# VISVESVARAYA TECHNOLOGICAL UNIVERSITY

Jnanasangama, Macche, Santibastwada Road
Belagavi-590018, Karnataka

**A**
**UG PROJECT REPORT**
on

# Multi-Signal Acquisition System for Health Monitoring

*Submitted in partial fulfillment of the requirement for the degree of*

**Bachelor of Engineering**
*in*
**Electronics & Communications Engineering - ECE**
*By*


| | |
|---|---|
| **1DS19EC117** | **Sai Sarthak S** |
| **1DS19EC130** | **Sirish Hublikar** |
| **1DS19EC131** | **Sohan Gowda R** |
| **1DS19EC134** | **Srikara Bharadwaj K S** |

Under the guidance
of

**Prof. Vidyashree K.N.**
Asst. Professor, ECE Dept., DSCE, Bengaluru

**Department of Electronics & Communication Engineering**
(An Autonomous College affiliated to VTU Belgaum, accredited by NBA & NAAC, Ranked by NIRF)
Shavige Malleshwara Hills, Kumaraswamy Layout,
Bengaluru-560078, Karnataka, India


**2022-23**

# Certificate

Certified that the project work entitled "**Multi-Signal Acquisition System for Health Monitoring**" carried out by **Sai Sarthak S** (1DS19EC117), **Sirish Hublikar** (1DS19EC130), **Sohan Gowda R** (1DS19EC131), **Srikara Bharadwaj K S** (1DS19EC134) are bonafide students of the ECE Dept. of Dayananda Sagar College of Engineering, Bangalore, Karnataka, India in partial fulfillment for the award of Bachelor of Engineering in Electronics & Communication Engineering of the Visvesvaraya Technological University, Belagavi, Karnataka during the academic year 2022-23. It is certified that all corrections / suggestions indicated for project work have been incorporated in the report deposited to the ECE department, the college central library & to the university. This final year project report **(Course Code: 19EC8ICPR2)** Phase-II has been approved as it satisfies the academic requirement in respect of project work prescribed for the said degree.

| | |
|---|---|
| Dept. Project Coordinators (Section in charges) | Project Guide |
| Prof. Bindu H M | Prof. Vidyashree K N |

| | |
|---|---|
| Head of the Department | Dr. B.G. Prasad |
| Dr. T. C. Manjunath, Ph.D. (IIT Bombay) | Principal, DSCE |

External Project Viva-Voce

Name of the project examiners with date:

1: Signature: ______________________

2: Signature: ______________________

# Declaration

Certified that the project work entitled, "**Multi-Signal Acquisition System for Health Monitoring** with the project work course code **19EC8ICPR2** is a bonafide work that was carried out by ourselves in partial fulfillment for the award of degree of Bachelor of Engineering in Electronics & Communication Engg. of the Visvesvaraya Technological University, Belagavi, Karnataka during the academic year 2022-23. We, the students of the project group/batch no. R22 do hereby declare that the entire project work has been done on our own & we have not copied or duplicated any other's work or maybe the extension of the works done by the earlier students. The results embedded in this UG project report have not been submitted elsewhere for the award of any type of undergraduate degree.

Student Name-1: Mr. Sai Sarthak S
USN: 1DS19EC117

Sign: ____________________

Student Name-2: Mr. Sirish Hublikar
USN: 1DS19EC130

Sign: ____________________

Student Name-3: Mr. Sohan Gowda R
USN: 1DS19EC131

Sign: ____________________

Student Name-4: Mr. Srikara Bharadwaj K S
USN: 1DS19EC134

Sign: ____________________

Date: 21/06/2023

Place: Bengaluru - 78

# Acknowledgement

As a team, we would like to extend our heartfelt gratitude and appreciation to the following individuals and entities who have played a significant role in our journey: First and foremost, we would like to express our deepest appreciation to Dr. Hemachandra Sagar, our esteemed Chairman. His visionary leadership and unwavering support have guided us through our endeavors, and we are immensely grateful for his contributions.

We are also grateful to Dr. Premachandra Sagar, our Vice Chairman, for his constant guidance and valuable insights. His wisdom and expertise have been instrumental in our growth and success. A special acknowledgement goes to Galiswamy, our dedicated Secretary, for his dedication and efforts in ensuring the smooth functioning of our initiatives. Her contributions have been vital to our accomplishments.

We extend our sincere appreciation to Tintisha Sagar, our Joint Secretary, for their collaboration and assistance. Their commitment and support have been truly commendable, and we are grateful for their contributions. We would like to express our gratitude to Dr. B.G. Prasad, our principal, for his constant support and encouragement. His guidance has been invaluable in shaping our academic journey.

Our heartfelt thanks go to Dr. T.C. Manjunath, our HOD, for his guidance and expertise. His mentorship has been instrumental in our professional development, and we are thankful for his contributions. We would like to acknowledge our Project Guide, Prof Vidyashree K N. Her guidance, knowledge, and continuous support throughout the project have been indispensable, and we are grateful for their contributions.

Our appreciation extends to Prof. Abhishek, Prof. Suma, Prof. Manasa, Prof. Srividya, and Bindu, our dedicated Dept. Project Coordinators. Their coordination and assistance have been pivotal in the successful completion of our projects, and we are grateful for their tireless efforts. We would like to thank all the teaching and non-teaching members of our department. Their dedication and hard work have created a conducive learning environment for us, and we appreciate their contributions.

We would like to express our deepest gratitude to our family members and relatives for their unwavering love, support, and belief in us. Their encouragement has been a constant source of strength, and we are grateful for their presence in our lives. To our friends, we are incredibly grateful for their unwavering support, motivation, and friendship.

Their presence has made our journey more joyful and fulfilling, and we appreciate their camaraderie. Lastly, we express our deepest gratitude to the Almighty. It is through His blessings, guidance, and grace that we have been able to navigate challenges, find inspiration, and achieve our goals. We acknowledge His role in our journey with humility and gratitude.

As a team, we are immensely thankful to each and every person and entity mentioned above, as well as anyone else who has contributed to our growth and success. Your support and belief in us have been instrumental in shaping our path, and we are truly grateful for your presence in our lives.

# Table of Contents

# List of Figures



# List of Tables

# Nomenclature and Acronyms

**Abbreviations:**

| | |
|---|---|
| CNN | Convolutional Neural Networks |
| ECG | Electrocardiogram |
| EEG | Electroencephalogram |
| EMG | Electromyogram |
| IEEE | Institute of Electrical & Electronics Engineers |
| Op-Amp | Operational Amplifier |
| SVM | Support Vector Machines |

# Abstract

In the field of human health care, it is important to have a health monitoring system in place. Health monitoring contributes to a wide variety of applications such as hospitals, home care units, sports training and emergency monitoring systems. This project aims to develop a device for acquiring three biomedical signals: **Electroencephalogram** (EEG), **Electrocardiogram** (ECG), and **Electromyogram** (EMG). The signals are obtained using electrodes placed on different parts of the body. The device focuses on arrhythmia detection using **SVM** with ECG signals and seizure detection using **CNN** with EEG signals. Additionally, the EMG signal is also acquired for further analysis. The ECG signal is processed using SVM to identify **Arrhythmias** by training the model on an annotated ECG dataset. Real-time detection and alerts are provided to detect abnormal heart rhythms. The EEG signal is analyzed using a CNN model trained on annotated EEG recordings to detect and predict **Seizure Activity.** Deep learning techniques allow the system to learn relevant features automatically, enhancing the accuracy of seizure detection. The project explores the potential of EMG signals in understanding muscular activity. EMG signals are acquired to gather insights into muscle contractions, fatigue, and movement patterns. The proposed device offers non-invasive, real-time monitoring of these physiological signals, enabling early detection and intervention. By providing timely alerts and insights, it has the potential to aid medical professionals in making informed decisions and improving patient outcomes. This project contributes to the field of biomedical signal analysis by providing a comprehensive solution for arrhythmia and seizure detection using SVM and CNN techniques. The integration of EMG signals adds an additional dimension to the analysis, expanding the understanding of muscular activity during these events.



**Keywords:**

*EEG: Electroencephalogram, ECG: Electrocardiogram, EMG: Electromyogram, SVM: Support Vector Machine, CNN: Convolutional neural network*

# Chapter-1

## Introduction

**Electroencephalography (EEG)** is a measurement of potentials that reflect the electrical activity of the human brain. It is a readily available test that provides evidence of how the brain functions over time. The EEG is widely used by physicians and scientists to study brain functions and to diagnose neurological disorders. The study of the brain's electrical activity, through the EEG records, is one of the most important tools for the diagnosis of neurological diseases, such as epilepsy, brain tumors, head injury, sleep disorders, dementia and monitoring the depth of anesthesia during surgery. It is also helpful for the treatment of abnormalities, behavioral disturbances (e.g., Autism), attention disorders, learning problems and language delay.

Frequency is one of the most important criteria for assessing abnormalities in clinical EEGs and for understanding functional behaviors in cognitive research. Frequency refers to rhythmic repetitive activity (in Hz). The number of cycles in a second is counted as frequency. With billions of oscillating communities of neurons as its source, human EEG potentials are manifested as aperiodic unpredictable oscillations with intermittent bursts of oscillations. In healthy adults, the amplitudes and frequencies of such signals change from one state to another, such as wakefulness and sleep. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies, respectively, are typically categorized in specific bands such as 0.5–4 Hz (delta, d), 4–8 Hz (Theta, h), 8–13 Hz (alpha, a), 13–30 Hz (beta, b) and >30 Hz (gamma, c). Higher frequencies are often more common in abnormal brain states such as epilepsy.

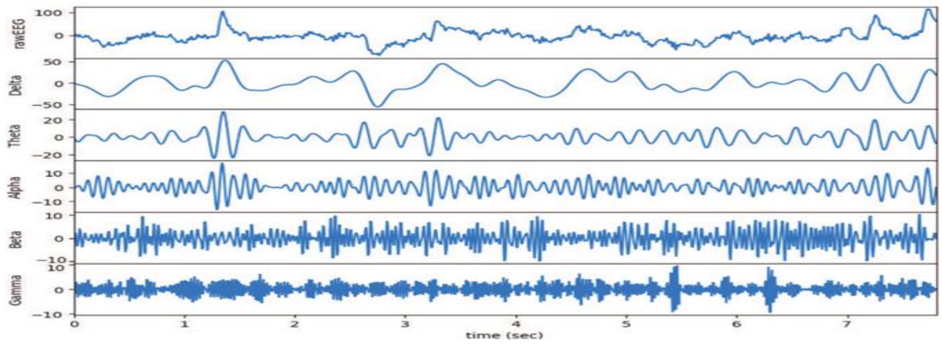



Fig1: Classified EEG Signals

The **Electro-Cardiogram (ECG)** is a useful tool to study functional and structural status of the heart. ECG is a recording of the bioelectrical potentials generated on the surface of the body by the heart. In 1901, Willem Einthoven used a string galvanometer to measure ECG and assigned letters P, Q, R, S and T to the various deflections. In recent years an automated method of analysis of ECG signals using real-time processing is very much required for the diagnosis of cardiac diseases accurately.

In a typical ECG tracing of the cardiac cycle (heartbeat) most of the energy is concentrated in QRS complex and very little energy in T wave and U wave, which is normally invisible in 50 to 75 % of ECGs because it is hidden by the T wave and upcoming new P wave. The type of wave and the action which causes them are summarized as the flat horizontal segments, PR segment and the segment between TP segments constitute the baseline of the electrocardiogram. In a normal healthy heart, the baseline is equivalent to the isoelectric line (0mV). However, in a diseased heart the baseline may be elevated (e.g., cardiac ischemia) or depressed (e.g., myocardial infarction) relative to the isoelectric line due to flow of injury currents during the conduction periods of the TP and PR intervals when the ventricles are at rest.
Normally the baseline drift caused by patient breathing, 50/60 Hz power line interference, bad electrodes and improper positioning of electrodes will corrupt ECG signal severely and make the detection of QRS complexes very difficult or may even lead to false detection. Different procedures and algorithms were developed by many researchers to detect QRS complexes accurately and precisely.

| **Wave** | **Action** |
|---|---|
| P-Wave | Depolarization of the atria |
| Q-Wave | Activation of the anteroseptal region of the ventricular myocardium |
| R-Wave | Depolarization of the ventricular myocardium |
| S-Wave | Activation of the posterobasal portion of the ventricles |
| T-Wave | Rapid ventricular repolarization |

Table 1: Types of waves and Action

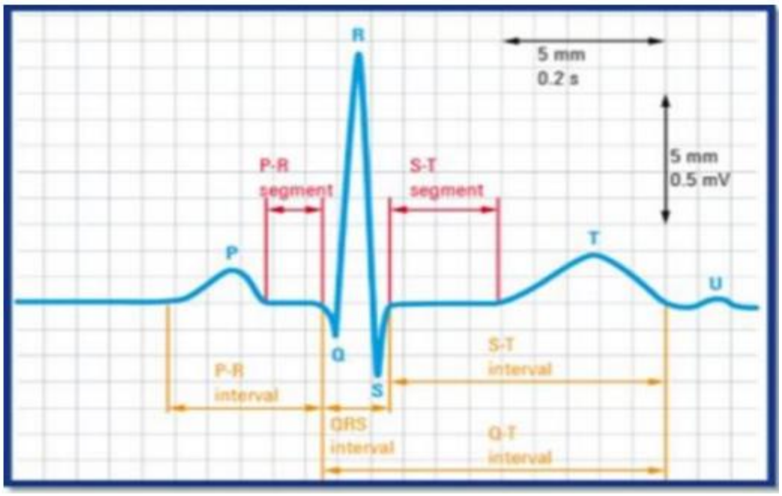



Fig 2: ECG Signal

**Electromyography (EMG)** is the study of the electrical activity of the muscle and is a valuable tool in the assessment of neuromuscular disorders. EMG findings are used to detect and describe different disease processes affecting the Motor Unit (MU), which is the smallest functional unit of the muscle. There are numerous neuromuscular disorders that influence the spinal cord, nerves or muscles. Early finding and diagnosis of these diseases by clinical examination and laboratory tests are crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling. This information is also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases.

The purpose of clinical electromyography (EMG) is to analyze the electrical activity from skeletal muscles during rest and during weak and maximal contraction. EMG signal is composed of motor unit action potentials (MUAPs)which is a compound signal generated by the muscle fibers of the MU, and its amplitude, duration, and shape vary in individual muscles according to the number of factors including the number of muscle fibers of the MU, the spatial distribution of endplates and the age of the subject. Furthermore, the individual muscle MUAPs vary, and it is insufficient to evaluate a single or a few MUAPs. Thus, MUAPs can be identified and tracked using pattern recognition techniques. The resulting information can be used to determine the origin of the disease, i.e., neuropathic or myopathic.

When a patient maintains a low level of muscle contraction, individual MUAPs can be easily recognized, since only a few MUs are active. As contraction intensity increases, more MUs are recruited; different MUAPs overlap, causing an interference pattern (i.e., superimposed MUAPs) EMG signal decomposition and MUAP classification into groups of similar shapes give significant information for the assessment of neuromuscular pathology. Recent advances in computer technology have made automated EMG analysis feasible. Many computer-based quantitative EMG analysis algorithms are commercially available or developed, but none of them are broadly accepted for widespread routine clinical use.

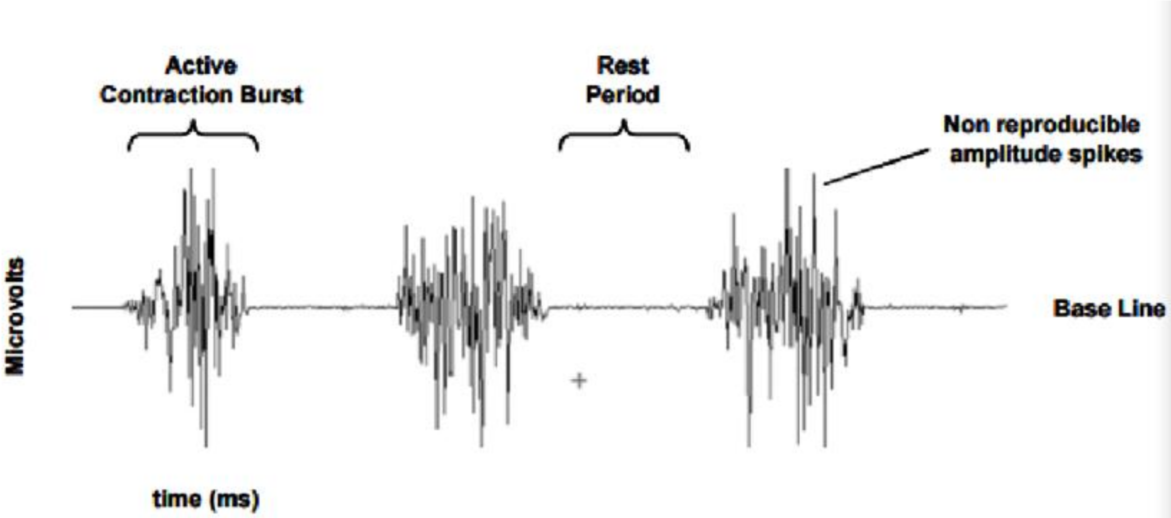



Fig 3: EMG signal

Bio signals can be measured using sensors such as electrodes that are skin surface transducers. Transducers are a device which converts one form of physical signal into an electric signal. The signal can be processed in electric circuits, that are bio electrodes, which are commonly used for measuring bio signals. In this proposed method, electrodes made up of silver-silver chloride metal are used.

Among the Bio Signal measuring devices, well known devices are electrocardiogram (ECG), electroencephalogram (EEG) and electromyogram (EMG). These signals are mainly used for applications like disease diagnosis. ECG signals are bipolar low frequency signals. The normal range of ECG signal is 0.05-100Hz having its amplitude range from 10 microvolt to 5 millivolts. 1mv is the typical value for ECG amplitude.

For EEG signals at low frequency 0.5-100Hz, 1-100 microvolt peak to peak is voltage range at cranial surface. ECG signal voltage is 100 times greater than EEG signal. So, EEG signals require input preamplifiers with high gain.

The information about frequency and voltage of signals from different measuring devices helps in diagnosis of the disease corresponding to the body part. Among them ECG is for diagnosing heart related diseases and disorders such as sudden cardiac arrest, cardiovascular diseases and so on. EEG measures bio potential generated by neural activity of the brain. It is more complex than ECG.

Arrhythmia is a cardiac condition characterized by abnormal heart rhythms, which can have serious health implications. Timely detection and accurate diagnosis of arrhythmia are crucial for effective medical intervention. Machine learning techniques, such as Support Vector Machines (SVM), have shown promise in automating the detection process using Electrocardiogram (ECG) signals. SVM is a supervised learning algorithm widely used for binary classification tasks. In arrhythmia detection, SVM analyzes ECG signals to differentiate between normal heart rhythms and abnormal patterns associated with arrhythmia. By extracting relevant features from the ECG signals and training on labeled datasets, the SVM model learns to classify new ECG signals and identify the presence of arrhythmia. The findings of this study contribute to the development of reliable arrhythmia detection methods, aiding in early diagnosis and effective management of this cardiac condition.

Seizures are sudden and abnormal electrical activities in the brain that can lead to various neurological disorders. Early detection and timely intervention are crucial for managing seizures and improving patient outcomes. Convolutional Neural Networks (CNN) has emerged as powerful tools for automatic seizure detection and classification using Electroencephalogram (EEG) signals. CNN is a deep learning algorithm designed for pattern recognition tasks, particularly effective in analyzing multidimensional data such as images or time-series signals like EEG. In the context of seizure detection, CNN models are trained on labeled EEG datasets to learn distinctive patterns associated with seizures.

By leveraging the hierarchical architecture of CNN, these models can automatically extract relevant features and accurately classify EEG signals as either seizure or non-seizure.

The outcomes of this study contribute to the development of reliable and efficient seizure detection systems, empowering healthcare professionals to make informed decisions and provide timely care for patients with epilepsy and other seizure-related disorders.

This report presents a comprehensive study on the acquisition and analysis of biomedical signals, specifically Electrocardiogram (ECG), Electroencephalogram (EEG), and Electromyogram (EMG), for the detection of arrhythmia and seizures. The aim is to develop a low-cost and portable Bio Signal acquisition system that is affordable and accessible in developing and underdeveloped countries. The study focuses on using SVM and ECG signals for arrhythmia detection, leveraging feature extraction techniques and robust classification algorithms. Additionally, CNN and EEG signals are utilized for seizure detection, employing preprocessing and deep learning methods. The integrated approach enables the acquisition of multiple signals using a single device, providing valuable insights for accurate diagnosis and timely intervention in healthcare settings.

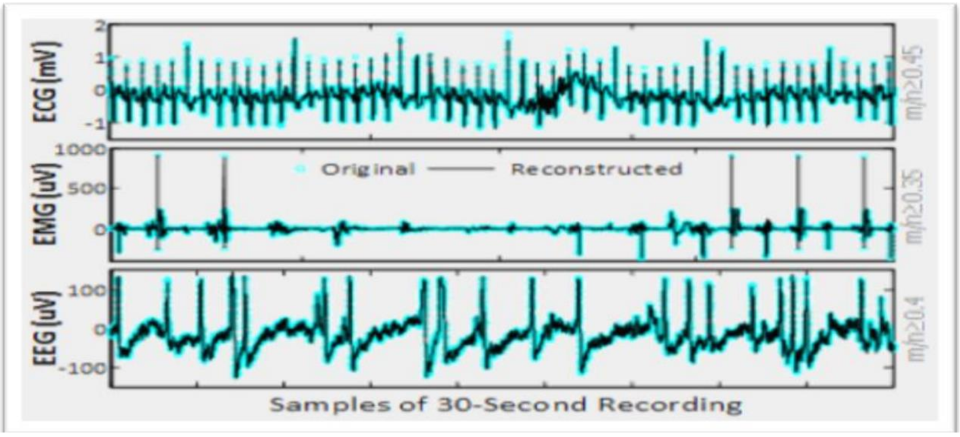



Fig 4: ECG, EMG and EEG Signals

## 1.1 Overview of the project work

The project involves the design of a device capable of acquiring three biomedical signals: Electroencephalogram (EEG), Electrocardiogram (ECG), and Electromyogram (EMG). The signals are captured using electrodes placed at different parts of the body. The ECG signal is utilized for arrhythmia detection using Support Vector Machines (SVM), which involves extracting relevant features and training a model to classify abnormal heart rhythms. On the other hand, the EEG signal is employed for seizure detection using Convolutional Neural Networks (CNN), which includes preprocessing the data and training a deep learning model to identify seizure patterns. Datasets are used to train and evaluate the SVM and CNN models, enabling accurate detection of arrhythmias and seizures. The project aims to provide a comprehensive and integrated solution for biomedical signal acquisition and analysis, facilitating early detection and intervention in medical settings.

## 1.2 Background information about the project work

The acquisition and analysis of biomedical signals, such as electroencephalogram (EEG) and electrocardiogram (ECG), play a crucial role in diagnosing and monitoring various medical conditions. EEG measures the electrical activity of the brain, providing insights into neurological disorders, while ECG measures the electrical activity of the heart, aiding in the detection and management of cardiac conditions. The development of a device capable of acquiring EEG and ECG signals, along with the integration of machine learning algorithms for arrhythmia and seizure detection, holds great promise for improving medical diagnostics and patient care.

Arrhythmias are abnormal heart rhythms that can lead to serious health complications, including cardiac arrest. Early detection and monitoring of arrhythmias are essential for timely intervention. ECG signals provide valuable information about the heart's electrical activity and can be analyzed to detect abnormal patterns associated with arrhythmias. By leveraging machine learning algorithms trained on a dataset of ECG signals with known arrhythmias, it becomes possible to accurately identify and classify different types of arrhythmias, enabling prompt medical intervention and tailored treatment plans. Seizures are sudden, uncontrolled electrical disturbances in the brain that can significantly impact a person's quality of life.

EEG signals offer a means to capture and analyze the electrical activity of the brain, aiding in the detection and characterization of seizures. Machine learning algorithms, when applied to EEG data, can learn patterns indicative of seizures and accurately identify seizure events. This allows for timely intervention, better management of seizures, and improved patient outcomes.

The integration of machine learning algorithms into the acquisition and analysis of EEG and ECG signals offers significant advancements in medical diagnostics. These algorithms can be trained on large datasets, encompassing a wide range of normal and abnormal signal patterns, enabling accurate and reliable detection of arrhythmias and seizures. By implementing a device that can acquire EEG and ECG signals, along with the associated machine learning algorithms, medical professionals can have a powerful tool for non-invasive monitoring, early detection, and effective management of these medical conditions. This technology has the potential to revolutionize patient care by improving diagnostic accuracy, facilitating personalized treatment plans, and ultimately enhancing patient outcomes.

## 1.3 Motivation obtained to take up the project work

The motivation for developing a device that acquires EEG, ECG, and EMG signals and utilizes them for arrhythmia and seizure detection lies in the need for accurate and timely diagnosis of these life-threatening conditions. In many healthcare settings, obtaining comprehensive and reliable data from multiple biomedical signals is essential for effective diagnosis and treatment planning. However, existing diagnostic devices are often expensive, bulky, and require specialized expertise for operation, making them inaccessible in resource-constrained environments or for individuals with limited financial means. By designing a cost-effective and user-friendly signal acquisition device capable of acquiring EEG, ECG, and EMG signals, we aim to bridge this gap and empower healthcare providers with a reliable tool for efficient arrhythmia and seizure detection. Our device, equipped with electrodes placed at various parts of the body, allows for convenient signal acquisition without the need for specialized electrode design. The acquired data is then processed using sophisticated algorithms and analyzed using SVM and CNN models trained on large datasets.

By enabling accurate and early detection of arrhythmias and seizures, our device has the potential to improve patient outcomes, facilitate timely intervention, and enhance the accessibility and affordability of diagnostic solutions, ultimately saving lives and contributing to improved healthcare delivery.

## 1.4 Problem statement of the project work

The acquisition and analysis of biomedical signals, such as electroencephalogram (EEG) and electrocardiogram (ECG), are critical for diagnosing and monitoring various medical conditions. However, there are several challenges and limitations that need to be addressed in the development of a comprehensive device capable of acquiring EEG and ECG signals and detecting arrhythmias and seizures.

**Lack of Accurate Diagnostic Tools:**

- There is a need for a reliable device that can provide accurate detection and monitoring of arrhythmias and seizures.

**Limited Monitoring Capabilities:**

- A non-invasive device that can offer continuous and real-time monitoring of these conditions is necessary.

**Complex Signal Analysis:**

- Analyzing EEG and ECG signals to detect abnormal patterns associated with arrhythmias and seizures is a complex task.

**Personalized Treatment Approach:**

- Arrhythmias and seizures exhibit significant variations among individuals, requiring personalized diagnosis and management.

**Integration of Machine Learning:**

- Challenges include data availability, standardization, and algorithm development for training the machine learning models.

Addressing these problem statements will contribute to the development of an advanced biomedical device capable of acquiring EEG and ECG signals, employing machine learning algorithms for accurate detection, and supporting personalized treatment approaches for improved patient care.

## 1.5 Objectives of the project work

The main objective of the project work is

- Design a device capable of acquiring three biomedical signals (EEG, ECG, EMG) from gel electrodes without distortion.
- Implement low pass, high pass, and notch filters to remove noise and enhance the quality of the acquired signals.
- Develop signal processing algorithms to effectively remove disturbances such as baseline wandering, further improving the signal quality.
- Utilize the ECG signal to detect arrhythmia using Support Vector Machines (SVM) for accurate classification of abnormal heart rhythms.
- Utilize the EEG signal to detect seizures using Convolutional Neural Networks (CNN) for identifying seizure patterns.
- Train the SVM and CNN models using appropriate datasets to ensure optimal performance in arrhythmia and seizure detection.
- Validate the device's performance by conducting thorough evaluations and comparing the results with existing methods.
- Provide a cost-effective solution for biomedical signal acquisition and analysis, especially beneficial in resource-limited or underdeveloped regions.
- Ultimately, enable early detection and intervention for arrhythmias and seizures, contributing to improved medical outcomes and patient care.

## 1.6 Scope of the project work

The scope of a Multi-Signal Acquisition System for Health Monitoring is quite extensive, as it plays a crucial role in monitoring and analyzing various physiological signals in real-time. Here are some key aspects of its scope:

1. **Healthcare and Medical Applications**: The Multi-Signal Acquisition System can be used in various healthcare and medical applications. It allows for the simultaneous acquisition and monitoring of multiple physiological signals, such as electrocardiogram (ECG), electromyogram (EMG), electroencephalogram (EEG), respiratory signals, and more. This system can assist in diagnosing and monitoring various medical conditions, including cardiovascular disorders, sleep disorders, neurological conditions, and respiratory diseases.

2. **Remote and Continuous Monitoring**: The system enables remote and continuous monitoring of patients' vital signs and physiological signals. It can be integrated with wireless communication technologies, allowing healthcare professionals to monitor patients remotely and receive real-time updates on their health status. This is particularly beneficial for patients in remote areas, those with chronic conditions, or individuals requiring long-term monitoring.

3. **Wearable Health Devices**: The Multi-Signal Acquisition System can be integrated into wearable health devices, such as smart watches, fitness trackers, or medical-grade wearables. This integration enables individuals to continuously monitor their health parameters, such as heart rate, sleep patterns, muscle activity, and respiratory rate. The system can provide insights into overall well-being, fitness levels, and potential health issues, empowering individuals to take proactive measures for their health management. Army or Air force vests can have these embedded for monitoring of their health conditions during various conditions of the environment.

4. **Sports and Performance Monitoring**: The system has applications in sports and performance monitoring. Athletes and fitness enthusiasts can utilize the system to monitor vital signs, muscle activity, and other physiological signals during training sessions or competitions. The acquired data can provide valuable insights into performance optimization, injury prevention, and recovery monitoring.

5. **Research and Development**: The Multi-Signal Acquisition System is essential for research and development in the healthcare domain. It allows researchers to gather data from multiple physiological signals simultaneously, facilitating comprehensive analysis and investigation. This data can be utilized to develop new diagnostic techniques, refine existing medical protocols, and improve understanding of complex physiological processes.

6. **Data Analysis and Machine Learning**: The system generates vast amounts of data, which can be further processed and analyzed using advanced algorithms and machine learning techniques. Data analysis can help identify patterns, detect anomalies, and extract meaningful insights from the acquired signals. This can lead to the development of predictive models, early warning systems, and personalized healthcare solutions.

In summary, the scope of a Multi-Signal Acquisition System for Health Monitoring encompasses various healthcare applications, remote monitoring, wearable devices, sports performance monitoring, research, and data analysis. It contributes to improved diagnostics, personalized healthcare, and a deeper understanding of human physiology.

## 1.7 Organization of the project report

**1. Chapter 1: Introduction**

Chapter 1 of the project report provides a concise overview of the project work. It introduces the reader to the project's scope, objectives, and significance, setting the stage for the subsequent chapters. The chapter also includes a brief background to establish the context for the research and development undertaken.

**2. Chapter 2: Literature Review**

Chapter 2 dives into a comprehensive literature review, summarizing the relevant works conducted by researchers and authors in the field. Drawing from a wide range of sources such as academic papers, articles, and books, the review identifies existing knowledge and research gaps. It provides a valuable understanding of the current state of the field and serves as a foundation for the project's further exploration and development.

**Chapter 3: Project Implementation and Tools**

This chapter focuses on the implementation details of the project, including the block diagram of the project's architecture and its working principle. It discusses the hardware and software tools used in the project and explains the process of interfacing different components. The chapter provides insights into the technical aspects of the project's implementation.

**Chapter 4: Results, Simulation, Advantages, Applications, and Limitations**

Chapter 4 presents the results obtained from the project, analyzing and interpreting them. It highlights the project's advantages compared to existing solutions and explores potential applications. The chapter also addresses any limitations or constraints of the project, providing a balanced evaluation of its capabilities.

**Chapter 5: Conclusion, Future Scope, and Outcomes**

This concluding chapter summarizes the key findings and outcomes of the project. It draws conclusions based on the analysis conducted and discusses the future scope of the project. The chapter explores potential areas for further research and development and provides recommendations for future implementation. It solidifies the project's contributions and outlines its potential impact.

After the references section, the project report includes the following points:

- Paper presentations in conferences during the tenure of the Project Work and paper publications in journals during the same period.
- Hard copies of the presented conference papers or published journal papers.
- Awards and recognitions received in Project Fests.
- Photographs, certificates, and any other visual documentation related to the project.
- Plagiarism report ensuring the originality of the project work.
- CO PO Mapping Sheet, showcasing how the project aligns with educational objectives.
- Budget estimation detailing the anticipated project expenses.

# Chapter 2

# Literature Survey

1. Wireless Health Monitoring System for ECG, EMG and EEG Detecting [1]c

In this paper, a wireless Bio Signal system was designed for health monitoring which integrates both the extracting and monitoring of the Bio Signal such as ECG, EEG and EMG. The developed integrating system is used for wireless monitoring of a patient's bio potential changes of the heart, neuronal activity of the brain and muscles of the body. The successful implementation of this wireless system helps to overcome the limitations of wired health monitoring systems.

2. Development of a Wearable EEG Device with a Low-Power Wireless Interface for Real-Time Monitoring [1]

This paper presents the development of a wearable EEG device with a low-power wireless interface for real-time monitoring. The device is designed to be small, lightweight, and comfortable to wear, and features a low-power Bluetooth interface for wireless data transmission. The paper also discusses the signal processing algorithms used to extract EEG features from the raw data, and evaluates the performance of the device in a series of experiments.

3. A Wearable Device for Monitoring Muscle Fatigue Based on Surface Electromyography [2]

This paper describes the development of a wearable device for monitoring muscle fatigue based on surface electromyography (EMG). The device consists of a wireless EMG sensor that can be attached to the skin over the muscles of interest, and a smartphone app that displays real-time data and provides feedback to the user. The paper discusses the signal processing algorithms used to analyze the EMG signals, and evaluates the performance of the device in a series of experiments.

4. Wearable Sensors for Monitoring of Fatigue in Muscles: A Systematic Review[3]

This paper provides a systematic review of wearable sensors for monitoring of fatigue in muscles. The review covers a range of wearable sensors, including EMG sensors, inertial sensors, and force sensors, and discusses their use for monitoring fatigue in different muscle groups. The paper also identifies key research challenges and opportunities for future development of wearable sensors for fatigue monitoring.

5. Wearable EMG Sensor for Assessment of Lumbar Spine Loads during Occupational Lifting Tasks [4]

This paper describes the development of a wearable EMG sensor for assessment of lumbar spine loads during occupational lifting tasks. The sensor consists of four EMG electrodes that are placed on the lower back muscles, and a wireless data acquisition system that can be worn on the waist. The paper discusses the signal processing algorithms used for assessment of lumbar spine loads, and evaluates the performance of the sensor in a series of experiments.

6. A Review on Wearable ECG Monitoring Systems: Design Challenges and Solutions [5]

This paper provides a comprehensive review of wearable ECG monitoring systems, including their design challenges and solutions. It discusses various factors that influence ECG signal quality, such as noise, motion artifacts, and electrode placement, and describes different approaches to mitigating these issues. The paper also reviews recent advances in wearable ECG devices, such as flexible and stretchable electronics, and discusses their potential applications in healthcare.

7. A Low-Power Wearable EEG Acquisition System for Real-Time Seizure Detection [6]

This paper presents a low-power wearable EEG acquisition system for real-time seizure detection. The device consists of a custom-built amplifier, a microcontroller, and a Bluetooth interface for wireless data transmission. The paper discusses the design considerations for the amplifier circuitry, the signal processing algorithms used for feature extraction and classification, and the performance of the device in a series of experiments.

8. Design and Implementation of a Wireless Wearable EMG System for Hand Gesture Recognition [7]

This paper describes the design and implementation of a wireless wearable EMG system for hand gesture recognition. The system consists of a wireless EMG sensor that can be attached to the skin over the forearm muscles, and a microcontroller that processes the EMG signals and classifies the hand gestures. The paper discusses the signal processing algorithms used for feature extraction and classification, and evaluates the performance of the system in a series of experiments.

9. A Wireless and Wearable ECG Monitoring System with Dynamic Threshold-Based Arrhythmia Detection [8]

This paper presents a wireless and wearable ECG monitoring system with dynamic threshold-based arrhythmia detection. The system consists of a wireless ECG sensor that can be attached to the skin, and a smartphone app that displays real-time data and provides alerts when arrhythmias are detected. The paper discusses the signal processing algorithms used for arrhythmia detection, and evaluates the performance of the system in a series of experiments.

10. Design and Development of an EEG Acquisition System for Wearable Applications [9]

This paper presents the design and development of an EEG acquisition system for wearable applications. The device consists of a custom-built amplifier, a microcontroller, and a Bluetooth interface for wireless data transmission. The paper discusses the design considerations for the amplifier circuitry, the signal processing algorithms used to extract EEG features from the raw data, and the performance of the device in a series of experiments.

11. EMG-Based Hand Gesture Recognition Using a Wearable Armband Sensor [10]

This paper describes the development of a wearable armband sensor for EMG-based hand gesture recognition. The device consists of eight surface EMG electrodes that are placed on the forearm and can capture signals from the muscles that control hand movements. The paper discusses the signal processing algorithms used to extract features from the EMG signals, and evaluates the performance of the device in a series of experiments.

In conclusion, Extensive research has been conducted on EEG, ECG, and EMG signals for arrhythmia and seizure detection, focusing on preprocessing techniques, machine learning algorithms (SVM, CNN), and diverse datasets to improve accuracy. Challenges like real-time processing and affordability require further exploration, but the literature survey provides a strong foundation for our reliable and accessible diagnostic device for cardiac and neurological conditions.

# Chapter 3

# Project Details

## 3.1 Block diagram of the proposed system

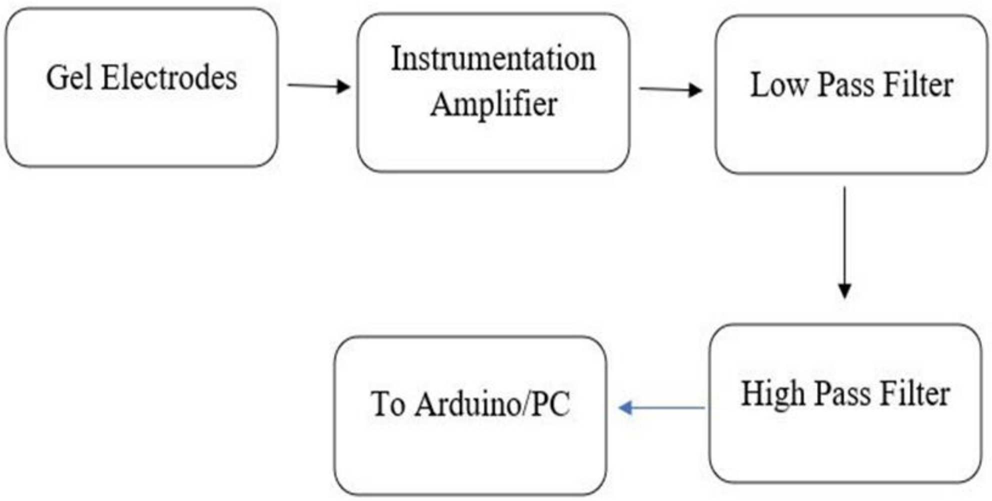



Fig. 5: Block-diagram of the proposed methodology

1. **Block 1: Bio Signal Electrodes (Gel)**

Bio signal electrodes are essential components used to capture the electrocardiogram (ECG) and electroencephalogram (EEG) signals from the body. These electrodes are placed on specific locations on the body, such as the chest for ECG or the scalp for EEG, ensuring accurate signal acquisition. Conductive gel is applied to the electrodes to establish a good electrical connection with the skin. This gel helps in reducing impedance and improving signal quality.

2. **Block 2: Instrumentation Amplifier**

The instrumentation amplifier plays a crucial role in amplifying the weak electrical signals captured by the bio signal electrodes. It enhances the signal strength, making it suitable for further processing and analysis. By amplifying the signals, the instrumentation amplifier improves the signal-to-noise ratio and minimizes any interference or noise that may be present during signal acquisition. This amplification ensures that the acquired signals are of sufficient amplitude for accurate analysis.

**3. Block 3: Low Pass Filter**

The low pass filter is used to remove high-frequency noise and artifacts from the amplified signals. It allows only the low-frequency components of the signals to pass through while attenuating or eliminating higher-frequency components. By doing so, the low pass filter helps in improving the signal quality by reducing noise and enhancing the relevant information for further analysis. It helps to smoothen the signal and eliminate high-frequency interference that may affect the accuracy of subsequent processing steps.

**4. Block 4: High Pass Filter**

The high pass filter is employed to eliminate low-frequency components, including baseline drift and other slow variations, from the amplified signals. It allows only the high-frequency components of the signals to pass through while attenuating or eliminating lower-frequency components. By doing so, the high pass filter helps in removing unwanted DC offsets, low-frequency interference, and baseline drift, thus enhancing the clarity of the signals for further processing and analysis.

**5. Block 5: Arduino/PC**

The Arduino or PC serves as the interface for data acquisition and processing. It receives the filtered and amplified signals from the previous blocks and digitizes them for further analysis. The Arduino or PC can store the acquired signals and transmit them to subsequent stages of the system for feature extraction, analysis, and detection. It provides the necessary computational power and storage capabilities to process the acquired biomedical signals, facilitating the implementation of advanced algorithms and techniques for arrhythmia and seizure detection.

## 3.2 Circuit diagram of the proposed system

The overall circuit diagram of the multi-signal acquisition device is shown in Fig. 6

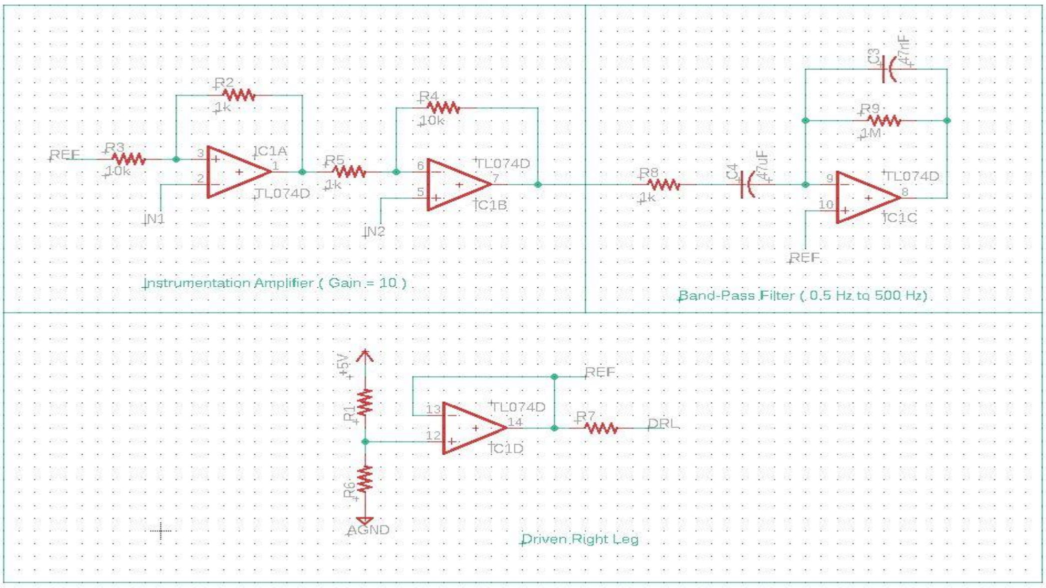



Fig. 6: Circuit Diagram

The circuit for acquiring biomedical signals utilizes the TL074 IC, a quad low-noise JFET-input operational amplifier. This IC is well-suited for signal amplification due to its low offset voltage, low noise, and high common-mode rejection ratio. The design of the instrumentation amplifier in this circuit deviates from the standard configuration. Instrumentation amplifiers with a gain of 8 are used. It incorporates an input filter to block DC and unwanted frequencies, ensuring that only the desired signals pass through. The differential gain amplifier amplifies the filtered signals with a specific gain and frequency range, enabling precise signal analysis. Second stage amplifier with a gain of about 100 is used.

To establish a stable output level, an amplifier reference is included, which sets the idle output at a predefined level, typically the midpoint of the supply voltage. This ensures that the amplified signals are properly centered and ready for further processing or analysis. Additionally, a driven right leg circuit is employed to eliminate common-mode signals. This circuit samples the common-mode voltage, amplifies it, and feeds it back to the body. This negative feedback mechanism effectively cancels out interference and unwanted signals that may be picked up by the electrodes, improving the overall signal quality.

## 3.3 Algorithm

Step1: Preprocess the ECG signals by applying a bandpass filter, performing baseline correction, and normalizing the signal.

Step2: Preprocess the EEG signals by applying a bandpass filter, performing artifact removal, and baseline correction and normalization.

Step3: Extract relevant features from the preprocessed ECG signals.

Step4: Extract relevant features from the preprocessed EEG signals.

Step5: Combine the extracted features from the ECG and EEG signals.

Step6: Train a machine learning model (SVM, CNN) using a labeled dataset of ECG and EEG signals with corresponding arrhythmia and seizure annotations.

Step7: Test the trained model on new, unseen data to predict the presence of arrhythmias and seizures.

Step8: Interpret the results of the model predictions.

## 3.4 Flow-chart / Data Flow Diagram

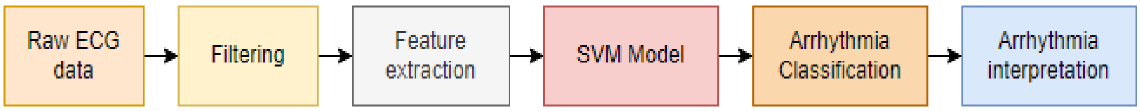



Fig. 7: Data Flow Diagram of Arrhythmia detection

The flow starts with acquiring raw ECG data, which is then preprocessed to remove noise and artifacts. Feature extraction is performed on the preprocessed signals to capture relevant characteristics indicative of arrhythmia. These features are then used as input for an SVM model, which classifies the ECG signals into different arrhythmia categories. The SVM model leverages learned patterns and relationships to make accurate arrhythmia classifications. The resulting arrhythmia classification is obtained and can be visualized or further analyzed for interpretation. This visualization provides a clear representation of detected arrhythmia segments or statistical summaries of the classification results. Overall, this flow encompasses the steps of data acquisition, preprocessing, feature extraction, SVM classification, and result visualization, enabling effective arrhythmia detection and aiding in the diagnosis and monitoring of heart conditions.

## 3.5 Flow-chart / Data Flow Diagram

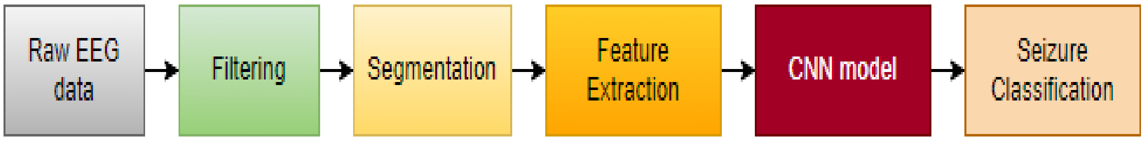



Fig. 8: Data Flow Diagram of Seizure detection

The flow starts with the acquisition of raw EEG data, representing the electrical activity of the brain. The data undergoes preprocessing to remove noise and artifacts, enhancing the quality of the signals for further analysis. Feature extraction follows, where relevant characteristics indicative of seizures is identified from the preprocessed EEG signals. These features serve as input to a Convolutional Neural Network (CNN) model, a deep learning algorithm capable of capturing complex patterns and relationships within the EEG data. The CNN model performs seizure classification based on the learned patterns, distinguishing between seizure and non-seizure activity in the EEG signals. The output of the CNN model is the seizure classification result, which can be visualized or further analyzed. Visualization techniques provide a clear representation of the detected seizure segments or statistical summaries of the classification results, aiding in the interpretation of the findings. This flow illustrates the steps involved in processing raw EEG data, extracting informative features, utilizing a CNN model for seizure classification, and visualizing the resulting seizure activity. Such an approach enables the identification and visualization of seizures in EEG signals, contributing to the diagnosis and monitoring of neurological conditions.

## 3.6 Hardware used

**Gel electrodes** are crucial for acquiring the bio signals from the body. These electrodes are designed to adhere to the skin and establish a reliable electrical connection with the underlying tissues. Gel electrodes provide good conductivity and minimize noise and interference, ensuring accurate signal acquisition.

The **TL074 Operational Amplifier** will be utilized as an instrumentation amplifier in conjunction with resistors and capacitors to amplify the bio signals acquired from the gel electrodes. The TL074 is known for its low noise, low distortion, and high gain bandwidth product, making it well-suited for amplification purposes in audio and precision instrumentation circuits. By configuring the operational amplifier as an instrumentation amplifier, it is possible to achieve high input impedance, low input bias current, and low input offset voltage, ensuring accurate and reliable amplification of the bio signals.

**Resistors and capacito**rs will be used in combination with the TL074 Operational Amplifier to set the gain and frequency response of the instrumentation amplifier circuit. The choice of resistors and capacitors will depend on the desired amplification factor, bandwidth, and other circuit parameters required for the specific application.

The **Arduino Uno** will play a vital role in the project by converting the analog bio signals into digital form using the Arduino Uno's built-in ADC (Analog-to-Digital Converter). The ADC of the Arduino Uno will sample the amplified analog signals and convert them into a digital representation, which can then be processed and analyzed by the microcontroller. This digital conversion enables further signal processing and analysis, such as filtering, feature extraction, and classification, which are essential for applications like arrhythmia detection and seizure identification.

Overall, this hardware setup allows for the amplification of bio signals using the TL074 Operational Amplifier and appropriate circuit components, followed by the conversion of these analog signals into digital form using the Arduino Uno's ADC. This combination of amplification and digital conversion facilitates subsequent signal processing and analysis, enabling applications such as arrhythmia detection and seizure identification.

## 3.7 Software used

**Arduino C** programming language will be utilized to acquire analog data from the hardware setup into the PC. Arduino C provides a simple and flexible platform for interfacing with the Arduino Uno microcontroller and enables the transfer of analog data to the PC for further processing and analysis.

**MATLAB**, a widely used programming and numerical computation software, will play a crucial role in the project. It will be used to apply filters such as high-pass, low-pass, and notch filters to denoise the acquired bio signals. MATLAB offers a comprehensive set of signal processing functions and tools that enable the design and implementation of various filters to enhance the quality of the signals. The filtering process aims to remove unwanted noise and artifacts, improving the accuracy of subsequent analysis steps.

**Spike Recorder software** will be utilized to record the bio signals as an audio file for further analysis. It provides a convenient way to capture and store the signals, allowing researchers and clinicians to review and analyze the data at a later time. The recorded audio files can be processed using various software tools or imported into other analysis environments for further investigation.

**Multisim**, circuit simulation software, may be employed in the project for circuit design and simulation purposes. It provides a virtual platform for designing and testing electronic circuits, allowing for a detailed analysis of circuit behavior and performance. Multisim can be used to validate the circuit design before implementing it in hardware, reducing the risk of errors and optimizing the performance of the overall system.

**Python programming language** will be used for the detection of arrhythmia and seizure using its libraries for machine learning and deep learning algorithms. Python offers a wide range of powerful libraries, such as Scikit-learn Tensor Flow, and Keras, which provide efficient implementations of various machine learning and deep learning algorithms. These algorithms can be trained on the acquired and preprocessed bio signal data to develop models for accurate arrhythmia and seizure detection.
Python's flexibility and extensive ecosystem make it a popular choice for implementing advanced data analysis and machine learning techniques.

In summary, the software tools selected for this project, including Arduino C, MATLAB, Spike Recorder, Multisim, and Python, enable various stages of data acquisition, filtering, recording, circuit simulation, and advanced data analysis. By leveraging these tools effectively, researchers can enhance the accuracy and reliability of the project's outcomes in terms of arrhythmia and seizure detection and analysis.

## 3.7 Interfacing

The interfacing issue with the signal from Arduino Uno to Arduino IDE's serial plotter not being properly visualized could be due to incorrect configuration or settings. It is important to ensure that the correct port and baud rate are selected in the Arduino IDE. Additionally, verifying the code for proper data transmission and formatting can help resolve this issue. Troubleshooting the connection between the Arduino board and the computer, such as checking the USB cable and the board's power supply, can also be beneficial in resolving any connectivity problems. The inability to record data directly from the serial monitor led to the adoption of an alternative solution using an application called Backyard Brains.

Backyard Brains is a tool that facilitates recording the data as an audio file. By utilizing this application, the analog data from the Arduino Uno's serial monitor can be converted into an audio signal and saved as an audio file for further processing. This approach provides an alternative means of capturing the data and bypasses the limitations of the serial monitor in terms of data recording. After obtaining the audio file recorded through Backyard Brains, the next step involved processing the data using MATLAB. MATLAB provides a wide range of functions and tools for signal processing, analysis, and visualization. The audio file can be imported into MATLAB, where various preprocessing techniques can be applied to clean and prepare the data for further analysis. Once the data is processed in MATLAB, it can be exported or saved in a format that can be easily utilized in Python for machine learning (ML) and deep learning (DL) models. Python, with its rich libraries such as Tensor Flow or PyTorch, offers a powerful environment for building, training, and evaluating ML and DL models using the preprocessed EEG data obtained from MATLAB.

## 3.8 Working principle of the proposed system

The proposed methodology encompasses two main aspects: the acquisition of biomedical signals and the detection of specific conditions using machine learning models.

For acquiring biomedical signals, the circuit design incorporates the TL074 IC, a low-noise JFET-input operational amplifier known for its performance in signal amplification. Instrumentation amplifiers with a gain of 8 are used, and an input filter is employed to block unwanted frequencies and DC offsets. The filtered signals are then amplified using a differential gain amplifier and a second stage amplifier. To ensure stability, an amplifier reference is included to set the output level at a predefined point. Additionally, a driven right leg circuit is implemented to eliminate common-mode signals, thereby improving overall signal quality.

In the arrhythmia detection methodology using ECG signals, the acquired ECG signals undergo preprocessing steps such as band pass filtering, baseline correction, and signal normalization. Relevant features indicative of arrhythmia, such as QRS complex duration and ST segment deviations, are extracted from the preprocessed signals. A Support Vector Machine (SVM) model is trained using labeled ECG data to learn patterns and relationships for classifying arrhythmias. The trained model is then applied to new, unseen ECG data to predict the presence of arrhythmias, with the results being visualized or further analyzed for interpretation.

In the seizure detection methodology using EEG signals, the acquired EEG signals are preprocessed through band pass filtering, artifact removal, and baseline correction and normalization. Informative features, such as spectral power or wavelet coefficients, are extracted from the preprocessed signals. A Convolutional Neural Network (CNN) model, capable of capturing complex patterns, is trained using labeled EEG data with seizure and non-seizure annotations. The CNN model distinguishes between seizure and non-seizure activity based on the extracted features. The trained model is then utilized to classify new EEG signals, and the seizure classification results can be visualized or further analyzed.

Overall, the proposed methodology involves signal acquisition, preprocessing, feature extraction, machine learning model training, and result visualization. It enables the effective detection of arrhythmias in ECG signals and identification of seizures in EEG signals, contributing to the diagnosis and monitoring of heart and neurological conditions.

## Overall Conclusions of the Chapter 3

In conclusion, the proposed methodology encompasses the acquisition of biomedical signals and the detection of specific conditions using machine learning models. The circuit design employs the TL074 IC and incorporates instrumentation amplifiers, filters, and amplifiers to ensure signal quality and stability. Preprocessing steps are applied to both ECG and EEG signals to remove noise and artifacts. Relevant features are then extracted from the preprocessed signals, and machine learning models (SVM for ECG and CNN for EEG) are trained to classify arrhythmias and seizures, respectively. The trained models are applied to new data for prediction, and the results can be visualized or further analyzed. The project also involves the use of software tools such as MATLAB, Spike Recorder, Multisim, Arduino C, and Python to facilitate signal acquisition, processing, and analysis. These tools enable filtering, recording, circuit simulation, and the implementation of advanced data analysis and machine learning techniques. By leveraging these methodologies and tools effectively, researchers can enhance the accuracy and reliability of arrhythmia and seizure detection, contributing to the diagnosis and monitoring of heart and neurological conditions.

# Chapter-4

# Results and Discussions

## 4.1 Simulation Results

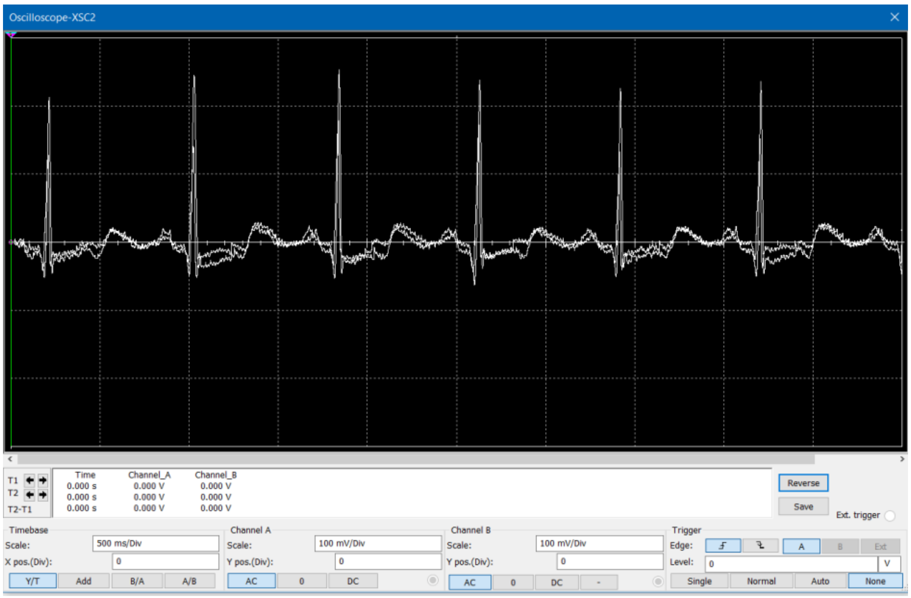



Fig 9: Raw Dataset waveform

The raw dataset was converted to a text file adding a time column, and its waveform was observed using an oscilloscope.

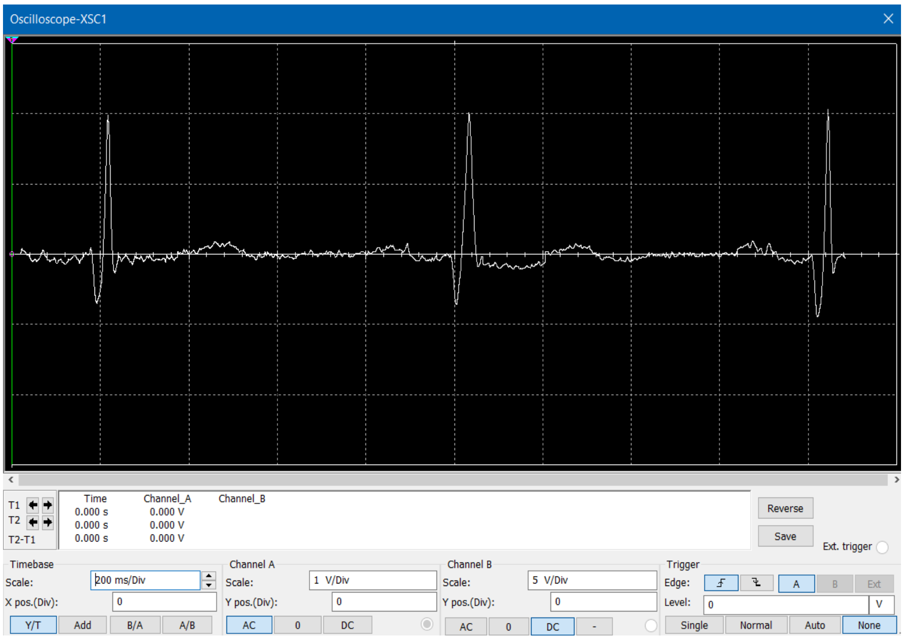



Fig 10: Output at instrumentation amplifier

The signal was given to an instrumentation amplifier of gain 11 db. The signal was amplified and the output was observed in the oscilloscope.

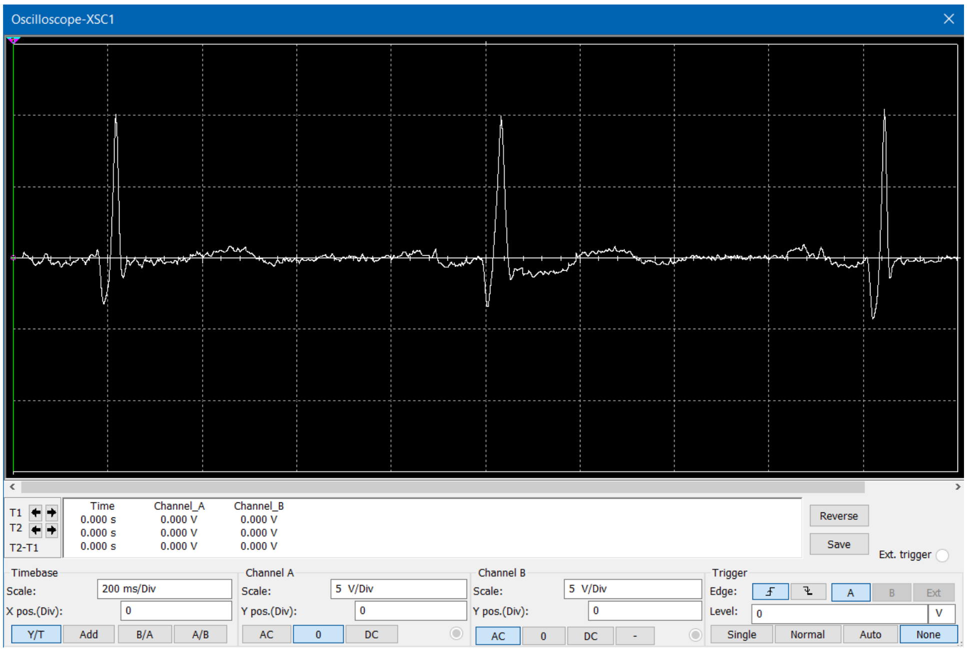



Fig 11: Output at high pass filter

The amplified signal was then given to a High Pass Filter having a cutoff frequency of 0.33 Hz. The output was observed in the oscilloscope.

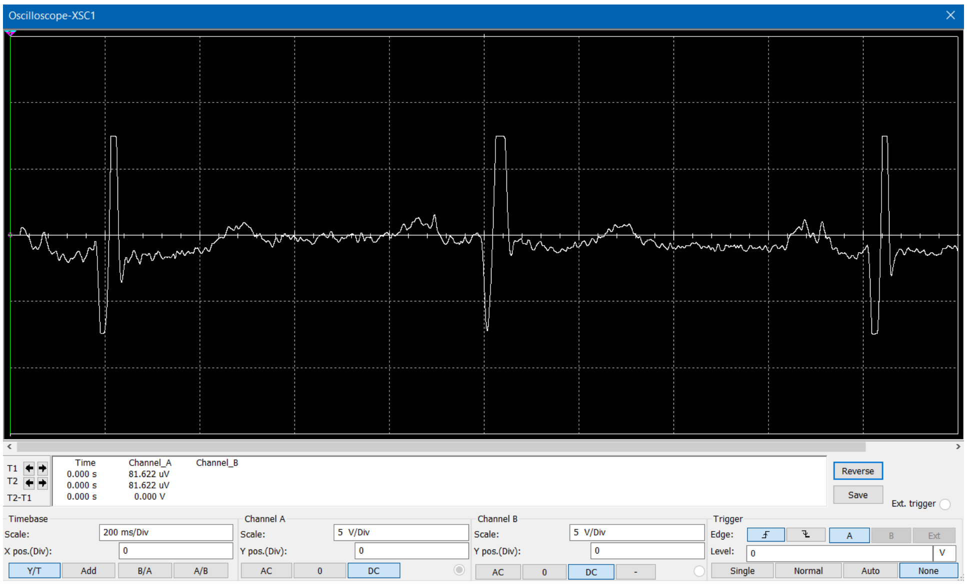



Fig 12: Output at Low Pass Filter

The output of the high pass filter was given to the active low pass filter having a cutoff frequency of 72.34 Hz. The output was observed in the oscilloscope.

## 4.2 Experimental Results

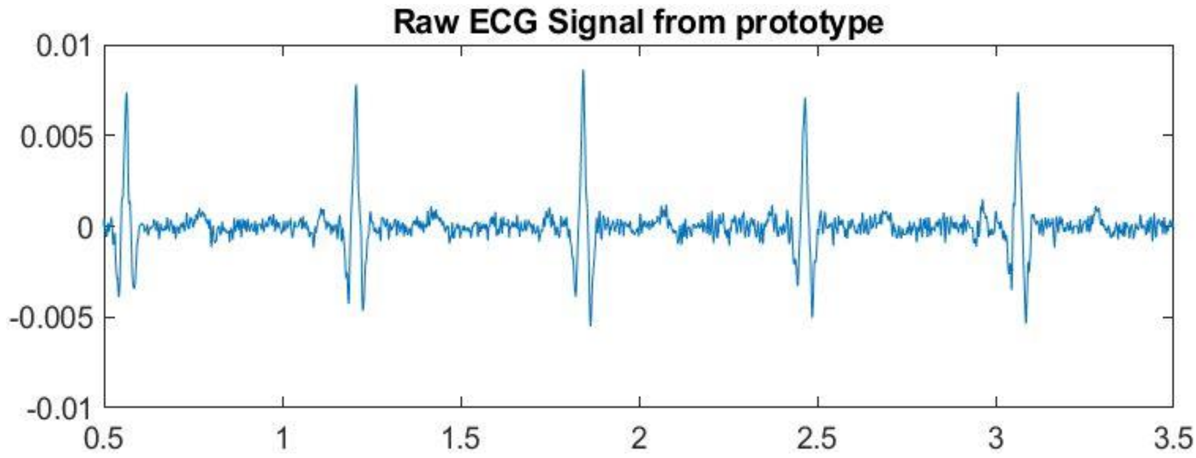



Fig 13: Recorded ECG signal from hardware

Recording of the ECG signal from the electrode is visualized on MATLAB. The signal is a raw signal with some noise. SNR (Signal to noise ratio) of about 20dB was obtained for the signal.

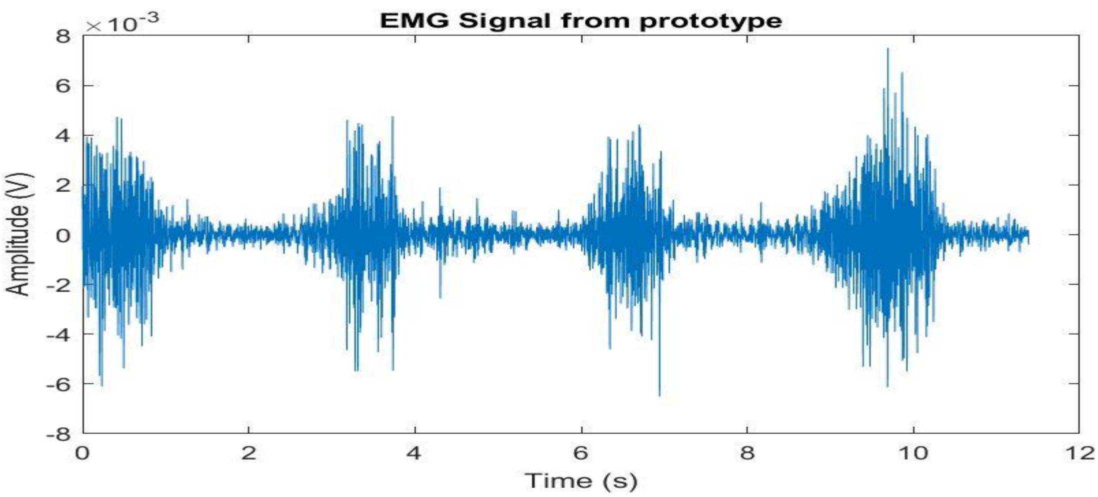



Fig 14: Recorded EMG signal from hardware

Recording of the EMG signal from the electrodes placed on the muscles is visualized on MATLAB. The signal depicts muscle contraction and relaxation.

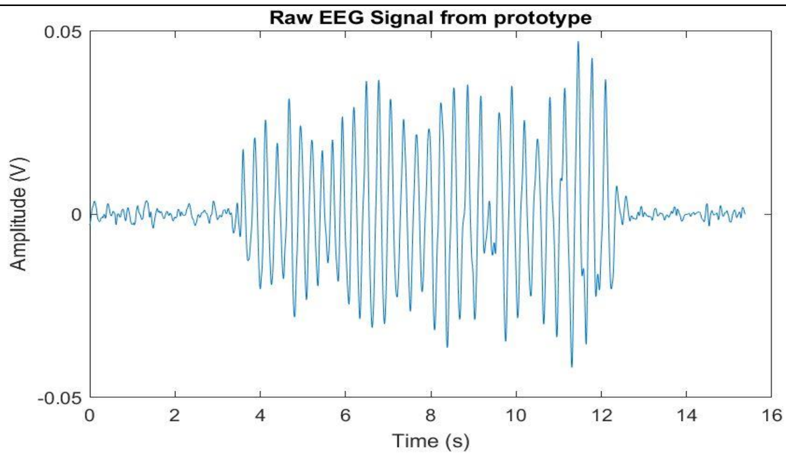



Fig 15: Recorded EEG signal from hardware

Recording of the EEG signal from the electrodes placed at the back of the ear is visualized on MATLAB. The signal belongs to the EEG signal in the Alpha region. SNR (Signal to noise ratio) of about 20dB was obtained for the signal.

ECG signals were further preprocessed on MATLAB and the signal was used in a trained SVM (Support Vector Machine) model to detect Arrhythmia. The model would output if Arrhythmia was detected or not on the basis of the intervals of the R-peak. EEG signals were also preprocessed on MATLAB for Seizure detection. Trained CNN (Convolution Neural Network) a deep learning algorithm was trained using datasets to detect Seizure from the obtained EEG signal.

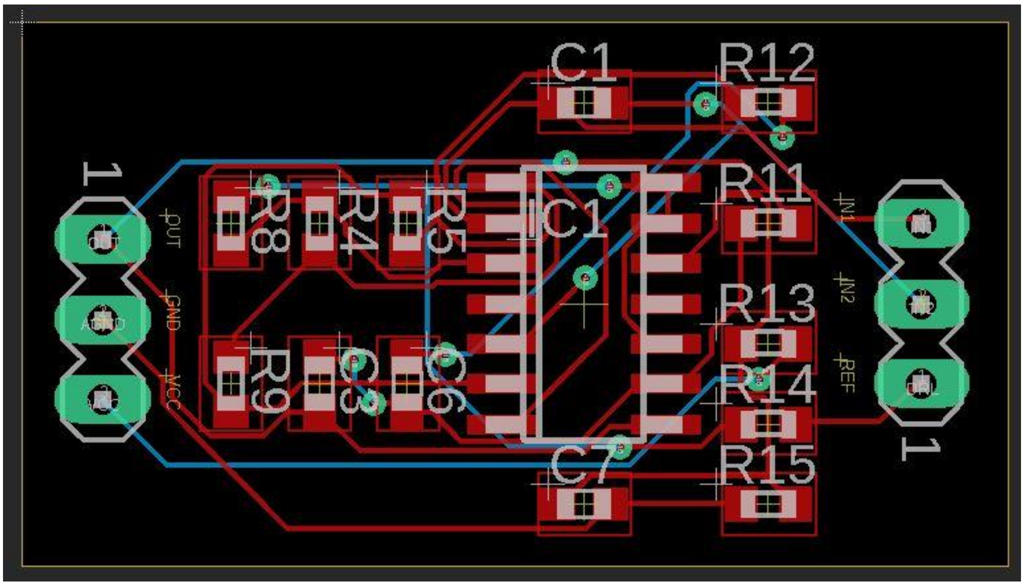



Fig 16: PCB layout

The layout for the PCB was designed in EAGLE PCB Design software**.**

## 4.3 Applications, Advantages, Limitations

**Advantages**:

- **Comprehensive Signal Acquisition**: The device acquires three important biomedical signals, namely EEG, ECG, and EMG, allowing for a holistic understanding of the body's electrical activity.
- **Efficient Arrhythmia Detection**: The use of Support Vector Machines (SVM) for arrhythmia detection ensures accurate classification of abnormal heart rhythms, enabling early identification and intervention.
- **Reliable Seizure Detection**: By leveraging Convolutional Neural Networks (CNN), the system can effectively detect seizures in EEG signals, providing timely alerts for medical intervention and patient safety.
- **Multi-Purpose Device**: The device serves multiple functions by acquiring and processing three distinct signals, enabling a wide range of applications in healthcare, research, and clinical settings.

**Applications**:

- **Clinical Diagnosis**: The device can be utilized in clinical settings for the early detection and diagnosis of arrhythmias and seizures, aiding healthcare professionals in providing timely and accurate treatment.
- **Remote Monitoring**: The portable nature of the device allows for remote monitoring of patients with arrhythmia or seizure disorders, facilitating continuous healthcare and reducing the need for frequent hospital visits.
- **Research and Development**: The acquired biomedical signals can be used in research studies to gain insights into the physiological processes associated with arrhythmias and seizures, leading to advancements in treatment and therapies.

**Limitations**:

- **Limited Signal Sources**: The device acquires signals from a specific set of electrodes placed on the body. While this provides valuable information, it may not capture certain localized or specific signals that require additional electrode placements.
- **Dependency on Training Data**: The accuracy of arrhythmia and seizure detection relies on the quality and diversity of the training datasets used to train the SVM and CNN models. Limited or biased training data may affect the system's performance.
- **False Positives/Negatives**: Like any diagnostic system, there is a possibility of false positives or false negatives in arrhythmia and seizure detection. The system's performance may vary depending on individual differences and specific physiological conditions.
- **Expertise and Interpretation**: Proper expertise is required for the interpretation of the acquired signals and the output generated by the SVM and CNN models. Trained professionals are needed to analyze and interpret the results accurately.

## 4.3 Conclusions of the chapter-4

In conclusion, the developed device and analysis techniques offer several advantages in the field of biomedical signal processing. It enables comprehensive signal acquisition, efficient arrhythmia detection using SVM, and reliable seizure detection using CNN. The device has applications in clinical diagnosis, remote monitoring, and research and development.

The advantages include the ability to acquire multiple biomedical signals, accurate classification of arrhythmias, timely seizure detection, and versatility in various healthcare settings. However, the device has limitations, such as dependency on training data quality, the possibility of false positives or negatives, the need for expertise in signal interpretation, and the limitation of signal sources.

Overall, this device and the associated algorithms provide a valuable tool for healthcare professionals, researchers, and remote monitoring applications. Further advancements and improvements can enhance the accuracy and effectiveness of arrhythmia and seizure detection, contributing to improved patient care and advancements in the field of biomedical signal analysis.

# Chapter-5

# Conclusions, Future Work & Scope of Project

## Conclusions

In conclusion, the development of a device capable of acquiring EEG, ECG, and EMG signals and utilizing SVM for arrhythmia detection and CNN for seizure detection holds immense promise for the field of healthcare. By employing three electrodes placed strategically on the body, this device enables the comprehensive capture of vital electrical signals, providing valuable insights into the body's physiological state.

The implementation of SVM and CNN algorithms enhances the diagnostic capabilities of the device, enabling accurate and efficient detection of arrhythmias and seizures. This breakthrough technology has the potential to revolutionize the early detection and monitoring of cardiac and neurological conditions, facilitating timely interventions and tailored treatment approaches.

The use of training datasets for model development and optimization ensures the robustness and reliability of the arrhythmia and seizure detection algorithms. However, it is important to acknowledge certain limitations, including the reliance on high-quality training data and the potential for false positives or negatives. The interpretation of acquired signals also requires expertise and careful analysis to ensure accurate diagnosis and appropriate medical interventions.

The applications of this device extend beyond clinical settings. It holds the potential to empower researchers, enabling them to conduct comprehensive studies and gather valuable data on the electrical activity of the body. Furthermore, its portability and cost-effectiveness make it accessible for use in developing and underdeveloped regions, addressing the limitations of existing expensive biomedical signal acquisition systems.

In summary, the device's ability to acquire three biomedical signals, detect arrhythmias using SVM, and identify seizures using CNN opens up new avenues in medical diagnostics and research. With further advancements and refinements, this technology has the potential to improve patient care, enhance disease management strategies, and contribute to the overall advancement of healthcare systems worldwide.

# Scope for future works in this domain

The domain of Multi-Signal Acquisition System for Health Monitoring holds immense potential for future works and advancements. Here are some potential areas of focus for future research and development:

1. **Integration of Additional Biomedical Signals**: While the current system acquires EEG, ECG, and EMG signals, there is room for incorporating other important biomedical signals. For example, integrating signals such as blood pressure, respiratory rate, or oxygen saturation levels can provide a more comprehensive understanding of a patient's health status.

2. **Real-time Analysis and Decision Support**: Enhancing the system to perform real-time analysis of acquired signals can enable immediate decision support for healthcare professionals. Implementing algorithms that can detect abnormalities or patterns indicative of critical conditions can provide timely interventions and improve patient outcomes.

3. **Personalized Healthcare Monitoring**: Developing algorithms and techniques that allow for personalized healthcare monitoring can be a promising direction. Customizing signal analysis based on an individual's baseline and specific health conditions can lead to more accurate detection of abnormalities and better personalized treatment plans.

4. **Wearable and Non-Invasive Devices**: Further miniaturization and development of wearable devices for multi-signal acquisition can enhance patient comfort and mobility. Designing non-invasive sensors and electrodes that can provide reliable signal acquisition without causing discomfort or skin irritation will improve usability and acceptance of the system.

5. **Long-Term Data Analysis and Predictive Modeling**: Collecting long-term data from patients using the multi-signal acquisition system can provide valuable insights into disease progression, treatment efficacy, and personalized health management. Applying machine learning techniques to analyze this longitudinal data can enable the development of predictive models for early disease detection and prognosis.

6. **Cloud-based Data Management and Analysis**: Utilizing cloud computing and storage solutions can enable efficient management and analysis of large volumes of data acquired by the multi-signal acquisition system. Cloud-based platforms can facilitate collaborative research, data sharing, and the development of large-scale databases for improved understanding and decision-making.

7. **Integration with Telemedicine and IoT Technologies**: Integrating the multi-signal acquisition system with telemedicine platforms and Internet of Things (IoT) technologies can enable remote patient monitoring and real-time data transmission. This integration can enhance the accessibility of healthcare services, facilitate teleconsultations, and enable seamless monitoring of patients in their home environments.

8. **Validation and Clinical Trials**: Conducting extensive validation studies and clinical trials to evaluate the performance and effectiveness of the multi-signal acquisition system in real-world scenarios will be crucial. Robust validation and clinical trials will provide the necessary evidence for regulatory approval and widespread adoption of the system.

Overall, the future of multi-signal acquisition systems for health monitoring lies in advancements such as incorporating additional signals, real-time analysis, personalization, wearability, long-term data analysis, cloud integration, telemedicine, and rigorous validation. Further research and innovation in these areas will contribute to improved healthcare outcomes, enhanced disease management, and more effective monitoring of patients' health conditions.

# Outcome of the project works

The project focuses on the development of a device capable of acquiring EEG, ECG, and EMG signals for health monitoring. The device utilizes SVM (Support Vector Machines) for arrhythmia detection and CNN (Convolutional Neural Network) for seizure detection. The goal is to revolutionize the early detection and monitoring of cardiac and neurological conditions, enabling timely interventions and tailored treatment approaches.

The implementation of SVM and CNN algorithms enhances the diagnostic capabilities of the device, enabling accurate and efficient detection of arrhythmias and seizures. By employing three strategically placed electrodes on the body, the device captures vital electrical signals, providing valuable insights into the body's physiological state.

The device's applications extend beyond clinical settings, empowering researchers to conduct comprehensive studies and gather valuable data on the body's electrical activity. Its portability and cost-effectiveness make it accessible for use in developing and underdeveloped regions, addressing the limitations of existing expensive biomedical signal acquisition systems.

While the project shows promise, there are certain limitations to consider. It relies on high-quality training data and there is a potential for false positives or negatives. The interpretation of acquired signals requires expertise and careful analysis to ensure accurate diagnosis and appropriate medical interventions.

# References


From text books –

[1]. Rangaraj M. Rangayyan, “**Biomedical Signal Analysis**”, *Wiley-IEEE Press 2002/2015*, Second Edition, 9781119068129, $125, April 2015.

From journal papers –

[1]. D. Kim, C. Song, J. Kim, and M. Kang, "**Development of a Wearable EEG Device with a Low-Power Wireless Interface for Real-Time Monitoring**," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-10, 2021.

[2]. A. Aissaoui, S. Gabouj, M. Boukadoum, and S. Charbonneau, "**A Wearable Device for Monitoring Muscle Fatigue Based on Surface Electromyography**," Sensors, vol. 21, p. 2313, 2021.

[3]. A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "**Wearable Sensors for Monitoring of Fatigue in Muscles: A Systematic Review**," Sensors, vol. 21, p. 642, 2021.

[4]. X. Li, W. Wan, and X. Lin, "**Wearable EMG Sensor for Assessment of Lumbar Spine Loads during Occupational Lifting Tasks**," Journal of Biomechanics, vol. 116, p. 110246, 2021.

[5]. H. Gholamhosseini, S. Nahavandi, A. Z. Kouzani, and M. Farhadi, "**A Review on Wearable ECG Monitoring Systems: Design Challenges and Solutions**," IEEE Reviews in Biomedical Engineering, vol. 13, pp. 144-158, 2020.

[6]. R. Khan, M. R. Islam, M. R. Islam, and M. H. Kabir, "**A Low-Power Wearable EEG Acquisition System for Real-Time Seizure Detection**," IEEE Transactions on Biomedical Circuits and Systems, vol. 14, pp. 1077-1088, 2020.

[7]. M. Haghparast, S. M. R. Golpayegani, and M. Al-Hussein, "**Design and Implementation of a Wireless Wearable EMG System for Hand Gesture Recognition**," IEEE Transactions on Instrumentation and Measurement, vol. 69, pp. 4988-4997, 2020.

[8]. M. T. Khan, S. C. Chan, and A. Hussain, "**A Wireless and Wearable ECG Monitoring System with Dynamic Threshold-Based Arrhythmia Detection**," Sensors, vol. 20, p. 2073, 2020.

[9]. R. Mahajan, A. Balasubramanian, P. M. Patil, and V. Sankaranarayanan, "**Design and Development of an EEG Acquisition System for Wearable Applications**," Journal of Medical Systems, vol. 43, p. 190, 2019.

[10]. F. Ghaderi, G. E. Faulkner, and B. G. Celler, "**EMG-Based Hand Gesture Recognition Using a Wearable Armband Sensor**," IEEE Sensors Journal, vol. 19, pp. 2668-2677, 2019.

[11]. Jiawei Xu; Srinjoy Mitra; Chris Van Hoof; Refet Firat Yazicioglu; Kofi A. A. Makinwa, "**Active Electrodes for Wearable EEG Acquisition: Review and Electronics Design Methodology**", IEEE Reviews in Biomedical Engineering, 28113349, Volume 10, 187-198, January 2019.

[12]. Nasir Faruk, Abubakar Abdulkarim, Ifada Emmanuel, Yusuf Y. Folawiyo, Kayode S. Adewole, Hammed A. Mojeed, Abdukareem A. Oloyede, Lukman A. Olawoyin, Ismaeel A. Sikiru, Musa Nehemiah, Abdulsalam Ya'u Gital, Haruna Chiroma, James A. Ogunmodede, Mubarak Almutairi, Ibraheem A. Katibi, "**A comprehensive survey on low-cost ECG acquisition systems: Advances on design specifications, challenges and future direction**", Elsevier Biocybernetics and Biomedical Engineering, Volume 41, Issue 2, 474-502, June 2021.

[13]. Danilo Ricciardi, Ilaria Cavallari, Antonio Creta, Giacomo Di Giovanni, Vito Calabrese, Natale Di Belardino, Simona Mega, Iginio Colaiori, Laura Ragni, Claudio Proscia, Antonio Nenna, Germano Di Sciascio, "**Impact of the high-frequency cutoff of bandpass filtering on ECG quality and clinical interpretation: A comparison between 40 Hz and 150 Hz cutoff in a surgical preoperative adult outpatient population**", Elsevier Journal of Electro cardiology, Volume 49, Issue 5, 691-695, October 2019.

From conference papers –

[1]. Ms. Nyni K.A, Linson K Vincent, Lisiya Varghese, Liya V.L, Neethu Johny A, Yesudas C. V, "**Wireless Health Monitoring System for ECG, EMG and EEG Detecting**", 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 17 March 2019.

[2]. David Alejandro Fernandez Guzman, Stefano Sapienza, Bianca Sereni, Paolo Motto Ros, "**Very low power event-based surface EMG acquisition system with off-the-shelf components**", IEEE Biomedical Circuits and Systems Conference (BioCAS), October 2020.

From websites –

[1]. https://www.youtube.com/watch?v=kiG7CyvRlcI&ab_channel=JimmyDieffenderfer

[2]. https://www.youtube.com/playlist?list=PLgMDNELGJ1CY-TT-BNLJbXCDqU9hpPF--

[3]. https://www.youtube.com/playlist?list=PLwjK_iyK4LLCQkfK92vdh3gAXoaOXXQDu

# Appendix

## Datasheet of the operational amplifier TL074 IC:

Ordering & quality | Technical documentation | Design & development | Support & training

TEXAS INSTRUMENTS

TL071, TL071A, TL071B, TL071H
TL072, TL072A, TL072B, TL072H, TL072M
TL074, TL074A, TL074B, TL074H, TL074M

SLOS080V – SEPTEMBER 1978 – REVISED APRIL 2023

### TL07xx Low-Noise FET-Input Operational Amplifiers

#### 1 Features

- High slew rate: 20 V/μs (TL07xH, typ)
- Low offset voltage: 1 mV (TL07xH, typ)
- Low offset voltage drift: 2 μV/°C
- Low power consumption: 940 μA/ch (TL07xH, typ)
- Wide common-mode and differential voltage ranges
  – Common-mode input voltage range includes $V_{CC+}$
- Low input bias and offset currents
- Low noise: $V_n$ = 18 nV/$\sqrt{Hz}$ (typ) at f = 1 kHz
- Output short-circuit protection
- Low total harmonic distortion: 0.003% (typ)
- Wide supply voltage: ±2.25 V to ±20 V, 4.5 V to 40 V

#### 2 Applications

- Solar energy: string and central inverter
- Motor drives: AC and servo drive control and power stage modules
- Single phase online UPS
- Three phase UPS
- Pro audio mixers
- Battery test equipment

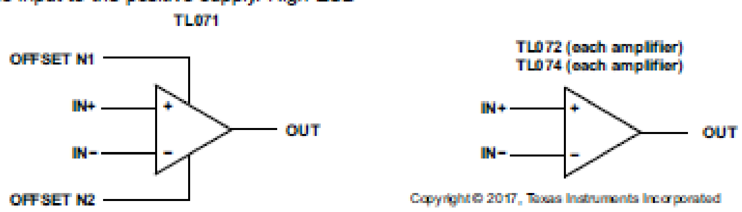
#### 3 Description

The TL07xH (TL071H, TL072H, and TL074H) family of devices are the next-generation versions of the industry-standard TL07x (TL071, TL072, and TL074) devices. These devices provide outstanding value for cost-sensitive applications, with features including low offset (1 mV, typical), high slew rate (20 V/μs), and common-mode input to the positive supply. High ESD (1.5 kV, HBM), integrated EMI and RF filters, and operation across the full –40°C to 125°C enable the TL07xH devices to be used in the most rugged and demanding applications.

**Package Information**

| PART NUMBER[1] | PACKAGE | BODY SIZE (NOM) |
|---|---|---|
| TL071x | P (PDIP, 8) | 9.59 mm × 6.35 mm |
| | DCK (SC70, 5) | 2.00 mm × 1.25 mm |
| | PS (SO, 8) | 6.20 mm × 5.30 mm |
| | D (SOIC, 8) | 4.90 mm × 3.90 mm |
| | DBV (SOT-23, 5) | 1.60 mm × 1.20 mm |
| TL072x | P (PDIP, 8) | 9.59 mm × 6.35 mm |
| | PS (SO, 8) | 6.20 mm × 5.30 mm |
| | D (SOIC, 8) | 4.90 mm × 3.90 mm |
| | P (SOT-23, 8) | 2.90 mm × 1.60 mm |
| | PW (TSSOP, 8) | 4.40 mm × 3.00 mm |
| TL072M | JG (CDIP , 8) | 9.59 mm × 6.67 mm |
| | W (CFP, 10) | 6.12 mm × 3.56 mm |
| | FK (LCCC, 20) | 8.89 mm × 8.89 mm |
| TL074x | N (PDIP, 14) | 19.30 mm × 6.35 mm |
| | NS (SO, 14) | 10.30 mm × 5.30 mm |
| | D (SOIC, 14) | 8.65 mm × 3.91 mm |
| | DYY (SOT-23, 14) | 4.20 mm × 2.00 mm |
| | DB (SSOP, 14) | 6.20 mm × 5.30 mm |
| | PW (TSSOP, 14) | 5.00 mm × 4.40 mm |
| TL074M | J (CDIP, 14) | 19.56 mm × 6.92 mm |
| | W (CFP, 14) | 9.21 mm × 6.29 mm |
| | FK (LCCC, 20) | 8.89 mm × 8.89 mm |

(1) For all available packages, see the orderable addendum at the end of the data sheet.




Logic Symbols

An IMPORTANT NOTICE at the end of this data sheet addresses availability, warranty, changes, use in safety-critical applications, intellectual property matters and other important disclaimers. PRODUCTION DATA.

## 6 Specifications

### 6.1 Absolute Maximum Ratings

over operating ambient temperature range (unless otherwise noted) [1]

| | | | MIN | MAX | UNIT |
|---|---|---|---|---|---|
| Supply voltage, $V_S = (V+) - (V-)$ | | All NS and PS packages; All TL07xM devices | −0.3 | 36 | V |
| | | All other devices | 0 | 42 | V |
| Signal input pins | Common-mode voltage [3] | All NS and PS packages; All TL07xM devices | (V−) − 0.3 | (V−) + 36 | V |
| | | All other devices | (V−) − 0.5 | (V+) + 0.5 | V |
| | Differential voltage [3] | All NS and PS packages; All TL07xM devices [4] | (V−) − 0.3 | (V−) + 36 | V |
| | | All other devices | | $V_S$ + 0.2 | V |
| | Current [3] | All NS and PS packages; All TL07xM devices | | 50 | mA |
| | | All other devices | −10 | 10 | mA |
| Output short-circuit [2] | | | Continuous | | |
| Operating ambient temperature, $T_A$ | | | −55 | 150 | °C |
| Junction temperature, $T_J$ | | | | 150 | °C |
| Case temperature for 60 seconds - FK package | | | | 260 | °C |
| Lead temperature 1.6 mm (1/16 inch) from case for 10 seconds | | | | 300 | °C |
| Storage temperature, $T_{stg}$ | | | −65 | 150 | °C |

(1) Stresses beyond those listed under *Absolute Maximum Ratings* may cause permanent damage to the device. These are stress ratings only, which do not imply functional operation of the device at these or any other conditions beyond those indicated under *Recommended Operating Conditions*. Exposure to absolute-maximum-rated conditions for extended periods may affect device reliability.
(2) Short-circuit to ground, one amplifier per package.
(3) Input pins are diode-clamped to the power-supply rails. Input signals that can swing more than 0.5 V beyond the supply rails must be current limited to 10 mA or less.
(4) Differential voltage only limited by input voltage.

### 6.2 ESD Ratings

| | | | VALUE | UNIT |
|---|---|---|---|---|
| $V_{(ESD)}$ | Electrostatic discharge | Human-body model (HBM), per ANSI/ESDA/JEDEC JS-001 [1] | ±2000 | V |
| | | Charged-device model (CDM), per JEDEC specification JESD22-C101 [2] | ±1000 | |

(1) JEDEC document JEP155 states that 500-V HBM allows safe manufacturing with a standard ESD control process.
(2) JEDEC document JEP157 states that 250-V CDM allows safe manufacturing with a standard ESD control process.

### 6.3 Recommended Operating Conditions

over operating ambient temperature range (unless otherwise noted)

| | | | MIN | MAX | UNIT |
|---|---|---|---|---|---|
| $V_S$ | Supply voltage, (V+) − (V−) | All NS and PS packages; All TL07xM devices [1] | 10 | 30 | V |
| | | All other devices | 4.5 | 40 | V |
| $V_I$ | Input voltage range | All NS and PS packages; All TL07xM devices | (V−) + 2 | (V+) + 0.1 | V |
| | | All other devices | (V−) + 4 | (V+) + 0.1 | V |
| $T_A$ | Specified temperature | TL07xM | −55 | 125 | °C |
| | | TL07xH | −40 | 125 | °C |
| | | TL07xI | −40 | 85 | °C |
| | | TL07xC | 0 | 70 | °C |

(1) V+ and V− are not required to be of equal magnitude, provided that the total $V_S$ (V+ − V−) is between 10 V and 30 V.

### 6.6 Thermal Information for Quad Channel

| THERMAL METRIC [1] | | TL074xx | | | | | | | | UNIT |
|---|---|---|---|---|---|---|---|---|---|---|
| | | D (SOIC) | DYY (SOT-23) | FK (TSSOP) | J (TSSOP) | N (TSSOP) | NS (TSSOP) | PW (TSSOP) | W (TSSOP) | |
| | | 14 PINS | 14 PINS | 20 PINS | 14 PINS | 14 PINS | 14 PINS | 14 PINS | 14 PINS | |
| $R_{\theta JA}$ | Junction-to-ambient thermal resistance | 114.2 | 153.2 | – | – | 80 | 76 | – | 128.8 | °C/W |
| $R_{\theta JC(top)}$ | Junction-to-case (top) thermal resistance | 70.3 | 88.7 | 5.61 | 14.5 | – | – | 14.5 | 56.1 | °C/W |
| $R_{\theta JB}$ | Junction-to-board thermal resistance | 70.2 | 65.4 | – | – | – | – | – | 127.6 | °C/W |
| $\psi_{JT}$ | Junction-to-top characterization parameter | 28.8 | 9.5 | – | – | – | – | – | 29 | °C/W |
| $\psi_{JB}$ | Junction-to-board characterization parameter | 69.8 | 65.0 | – | – | – | – | – | 106.1 | °C/W |
| $R_{\theta JC(bot)}$ | Junction-to-case (bottom) thermal resistance | N/A | N/A | – | – | – | – | – | 0.5 | °C/W |

(1) For more information about traditional and new thermal metrics, see the *Semiconductor and IC Package Thermal Metrics* application report, SPRA953.

TEXAS INSTRUMENTS
www.ti.com

**TL071, TL071A, TL071B, TL071H**
**TL072, TL072A, TL072B, TL072H, TL072M**
**TL074, TL074A, TL074B, TL074H, TL074M**
SLOS080V – SEPTEMBER 1978 – REVISED APRIL 2023

### 6.7 Electrical Characteristics: TL07xH

For $V_S = (V_{CC+}) - (V_{CC-})$ = 4.5 V to 40 V (±2.25 V to ±20 V) at $T_A$ = 25°C, $R_L$ = 10 kΩ connected to $V_S$ / 2, $V_{CM} = V_S$ / 2, and $V_{OUT} = V_S$ / 2, unless otherwise noted.

| PARAMETER | | TEST CONDITIONS | | MIN | TYP | MAX | UNIT |
|---|---|---|---|---|---|---|---|
| **OFFSET VOLTAGE** | | | | | | | |
| $V_{OS}$ | Input offset voltage | | | | ±1 | ±4 | mV |
| | | | $T_A$ = –40°C to 125°C | | | ±5 | mV |
| $dV_{OS}/dT$ | Input offset voltage drift | | $T_A$ = –40°C to 125°C | | ±2 | | µV/°C |
| PSRR | Input offset voltage versus power supply | $V_S$ = 5 V to 40 V, $V_{CM} = V_S$ / 2 | $T_A$ = –40°C to 125°C | | ±1 | ±10 | µV/V |
| | Channel separation | f = 0 Hz | | | 10 | | µV/V |
| **INPUT BIAS CURRENT** | | | | | | | |
| $I_B$ | Input bias current | | | | ±1 | ±120 | pA |
| | | | DCK and DBV packages | | ±1 | ±300 | pA |
| | | | $T_A$ = –40°C to 125°C [1] | | | ±5 | nA |
| $I_{OS}$ | Input offset current | | | | ±0.5 | ±120 | pA |
| | | | DCK and DBV packages | | ±0.5 | ±250 | pA |
| | | | $T_A$ = –40°C to 125°C [1] | | | ±5 | nA |
| **NOISE** | | | | | | | |
| $E_N$ | Input voltage noise | f = 0.1 Hz to 10 Hz | | | 9.2 | | $µV_{PP}$ |
| | | | | | 1.4 | | $µV_{RMS}$ |
| $e_N$ | Input voltage noise density | f = 1 kHz | | | 37 | | $nV/\sqrt{Hz}$ |
| | | f = 10 kHz | | | 21 | | $nV/\sqrt{Hz}$ |
| $i_N$ | Input current noise | f = 1 kHz | | | 80 | | $fA/\sqrt{Hz}$ |
| **INPUT VOLTAGE RANGE** | | | | | | | |
| $V_{CM}$ | Common-mode voltage range | | | $(V_{CC-})$ + 1.5 | | $(V_{CC+})$ | V |
| CMRR | Common-mode rejection ratio | $V_S$ = 40 V, $(V_{CC-})$ + 2.5 V < $V_{CM}$ < $(V_{CC+})$ – 1.5 V | | 100 | 105 | | dB |
| | | | $T_A$ = –40°C to 125°C | 95 | | | dB |
| | | $V_S$ = 40 V, $(V_{CC-})$ + 2.5 V < $V_{CM}$ < $(V_{CC+})$ | | 90 | 105 | | dB |
| | | | $T_A$ = –40°C to 125°C | 80 | | | dB |
| **INPUT CAPACITANCE** | | | | | | | |
| $Z_{ID}$ | Differential | | | | 100 \|\| 2 | | MΩ \|\| pF |
| $Z_{ICM}$ | Common-mode | | | | 6 \|\| 1 | | TΩ \|\| pF |
| **OPEN-LOOP GAIN** | | | | | | | |
| $A_{OL}$ | Open-loop voltage gain | $V_S$ = 40 V, $V_{CM} = V_S$ / 2, $(V_{CC-})$ + 0.3 V < $V_O$ < $(V_{CC+})$ – 0.3 V | $T_A$ = –40°C to 125°C | 118 | 125 | | dB |
| $A_{OL}$ | Open-loop voltage gain | $V_S$ = 40 V, $V_{CM} = V_S$ / 2, $R_L$ = 2 kΩ, $(V_{CC-})$ + 1.2 V < $V_O$ < $(V_{CC+})$ – 1.2 V | $T_A$ = –40°C to 125°C | 115 | 120 | | dB |
| **FREQUENCY RESPONSE** | | | | | | | |
| GBW | Gain-bandwidth product | | | | 5.25 | | MHz |
| SR | Slew rate | $V_S$ = 40 V, G = +1, $C_L$ = 20 pF | | | 20 | | V/µs |
| $t_S$ | Settling time | To 0.1%, $V_S$ = 40 V, $V_{STEP}$ = 10 V , G = +1, CL = 20 pF | | | 0.63 | | µs |
| | | To 0.1%, $V_S$ = 40 V, $V_{STEP}$ = 2 V , G = +1, CL = 20 pF | | | 0.56 | | µs |
| | | To 0.01%, $V_S$ = 40 V, $V_{STEP}$ = 10 V , G = +1, CL = 20 pF | | | 0.91 | | µs |
| | | To 0.01%, $V_S$ = 40 V, $V_{STEP}$ = 2 V , G = +1, CL = 20 pF | | | 0.48 | | µs |
| | Phase margin | G = +1, $R_L$ = 10 kΩ, $C_L$ = 20 pF | | | 56 | | ° |
| | Overload recovery time | $V_{IN}$ X gain > $V_S$ | | | 300 | | ns |
| THD+N | Total harmonic distortion + noise | $V_S$ = 40 V, $V_O$ = 6 $V_{RMS}$, G = +1, f = 1 kHz | | | 0.00012 | | % |
| EMIRR | EMI rejection ratio | f = 1 GHz | | | 53 | | dB |
| **OUTPUT** | | | | | | | |


Submit Document Feedback 15

Product Folder Links: TL071 TL071A TL071B TL071H TL072 TL072A TL072B TL072H TL072M TL074 TL074A TL074B TL074H TL074M

## 6.7 Electrical Characteristics: TL07xH (continued)

For $V_S = (V_{CC+}) – (V_{CC–})$ = 4.5 V to 40 V (±2.25 V to ±20 V) at $T_A$ = 25°C, $R_L$ = 10 kΩ connected to $V_S$ / 2, $V_{CM}$ = $V_S$ / 2, and $V_{O\ UT}$ = $V_S$ / 2, unless otherwise noted.

| PARAMETER | | TEST CONDITIONS | | MIN | TYP | MAX | UNIT |
|---|---|---|---|---|---|---|---|
| | Voltage output swing from rail | Positive rail headroom | $V_S$ = 40 V, $R_L$ = 10 kΩ | | 115 | 210 | mV |
| | | | $V_S$ = 40 V, $R_L$ = 2 kΩ | | 520 | 965 | |
| | | Negative rail headroom | $V_S$ = 40 V, $R_L$ = 10 kΩ | | 105 | 215 | |
| | | | $V_S$ = 40 V, $R_L$ = 2 kΩ | | 500 | 1030 | |
| $I_{SC}$ | Short-circuit current | | | | ±26 | | mA |
| $C_{LOAD}$ | Capacitive load drive | | | | 300 | | pF |
| $Z_O$ | Open-loop output impedance | f = 1 MHz, $I_O$ = 0 A | | | 125 | | Ω |
| POWER SUPPLY | | | | | | | |
| $I_Q$ | Quiescent current per amplifier | $I_O$ = 0 A | | | 937.5 | 1125 | µA |
| | | $I_O$ = 0 A, (TL071H) | | | 960 | 1156 | |
| | | $I_O$ = 0 A | $T_A$ = –40°C to 125°C | | | 1130 | |
| | | $I_O$ = 0 A, (TL072H) | | | | 1143 | |
| | | $I_O$ = 0 A, (TL071H) | | | | 1160 | |
| | Turn-On Time | At $T_A$ = 25°C, $V_S$ = 40 V, $V_S$ ramp rate > 0.3 V/µs | | | 60 | | µs |

(1) Max $I_B$ and $I_{OS}$ data is specified based on characterization results.

### 6.8 Electrical Characteristics (DC): TL07xC, TL07xAC, TL07xBC, TL07xI, TL07xM

For $V_S = (V_{CC+}) - (V_{CC-}) = \pm15$ V at $T_A = 25°C$, unless otherwise noted

| PARAMETER | | TEST CONDITIONS[(1) (2)] | | | MIN | TYP | MAX | UNIT |
|---|---|---|---|---|---|---|---|---|
| $V_{OS}$ | Input offset voltage | $V_O = 0$ V, $R_S = 50\ \Omega$ | TL07xC | | | 3 | 10 | mV |
| | | | | $T_A$ = Full range | | | 13 | |
| | | | TL07xAC | | | 3 | 6 | |
| | | | | $T_A$ = Full range | | | 7.5 | |
| | | | TL07xBC | | | 2 | 3 | |
| | | | | $T_A$ = Full range | | | 5 | |
| | | | TL07xI | | | 3 | 6 | |
| | | | | $T_A$ = Full range | | | 8 | |
| | | | TL071M, TL072M | | | 3 | 6 | |
| | | | | $T_A$ = Full range | | | 9 | |
| | | | TL074M | | | 3 | 9 | |
| | | | | $T_A$ = Full range | | | 15 | |
| $dV_{OS}/dT$ | Input offset voltage drift | $V_O = 0$ V, $R_S = 50\ \Omega$ | $T_A$ = Full range | | | ±18 | | μV/°C |
| $I_{OS}$ | Input offset current | $V_O = 0$ V | TL07xC | | | 5 | 100 | pA |
| | | | | $T_A$ = Full range | | | 10 | nA |
| | | | TL07xAC, TL07xBC, TL07xI | | | 5 | 100 | pA |
| | | | | $T_A$ = Full range | | | 2 | nA |
| | | | TL07xM | | | 5 | 100 | pA |
| | | | | $T_A$ = Full range | | | 20 | nA |
| $I_B$ | Input bias current | $V_O = 0$ V | TL07xC, TL07xAC, TL07xBC, TL07xI | | | 65 | 200 | pA |
| | | | | $T_A$ = Full range | | | 7 | nA |
| | | | TL071M, TL072M | | | 65 | 200 | pA |
| | | | | $T_A$ = Full range | | | 50 | nA |
| | | | TL074M | | | 65 | 200 | pA |
| | | | | $T_A$ = Full range | | | 20 | nA |
| $V_{CM}$ | Common-mode voltage range | | | | ±11 | −12 to 15 | | V |
| VOM | Maximum peak output voltage swing | $R_L = 10$ kΩ | | | ±12 | ±13.5 | | V |
| | | $R_L \geq 10$ kΩ | $T_A$ = Full range | | ±12 | | | |
| | | $R_L \geq 2$ kΩ | | | ±10 | | | |
| $A_{OL}$ | Open-loop voltage gain | $V_O = 0$ V | TL07xC | | 25 | 200 | | V/mV |
| | | | | $T_A$ = Full range | 15 | | | |
| | | | TL07xAC, TL07xBC, TL07xI | | 50 | 200 | | |
| | | | | $T_A$ = Full range | 25 | | | |
| | | | TL07xM | | 35 | 200 | | |
| | | | | $T_A$ = Full range | 15 | | | |
| GBW | Gain-bandwidth product | All NS and PS packages; All TL07xM devices | | | | 3 | | MHz |
| | | All other devices | | | | 5.25 | | |
| $R_{ID}$ | Common-mode input resistance | | | | | 1 | | TΩ |
| CMRR | Common-mode rejection ratio | $V_{IC} = V_{ICR(min)}$, $V_O = 0$ V, $R_S = 50\ \Omega$ | TL07xC | | 70 | 100 | | dB |
| | | | TL07xAC, TL07xBC, TL07xI | | 75 | 100 | | |
| | | | TL07xM | | 80 | 86 | | |
| PSRR | Input offset voltage versus power supply | $V_S = \pm9$ V to $\pm18$ V, $V_O = 0$ V, $R_S = 50\ \Omega$ | TL07xC | | 70 | 100 | | dB |
| | | | TL07xAC, TL07xBC, TL07xI | | 80 | 100 | | |
| | | | TL07xM | | 80 | 86 | | |
| $I_Q$ | Quiescent current per amplifier | $V_O = 0$ V; no load | | | | 1.4 | 2.5 | mA |

## 6.9 Electrical Characteristics (AC): TL07xC, TL07xAC, TL07xBC, TL07xI, TL07xM

For $V_S = (V_{CC+}) – (V_{CC–}) = ±15$ V at $T_A = 25°C$, unless otherwise noted.

| PARAMETER | | TEST CONDITIONS | | MIN | TYP | MAX | UNIT |
|---|---|---|---|---|---|---|---|
| SR | Slew rate | $V_I$ = 10 V, $C_L$ = 100 pF, $R_L$ = 2 kΩ | TL07xM | 5 | 20 | | V/µs |
| | | | TL07xC, TL07xAC, TL07xBC, TL07xI | 8 | 20 | | V/µs |
| $t_s$ | Settling time | $V_I$ = 20 V, $C_L$ = 100 pF, $R_L$ = 2 kΩ | | | 0.1 | | µs |
| | | | | | 20% | | |
| $e_N$ | Input voltage noise density | All PS and NS packages; All TL07xM devices | $R_S$ = 20 Ω, f = 1 kHz | | 18 | | nV/√Hz |
| | | All other devices | f = 1 kHz | | 37 | | nV/√Hz |
| | | | f = 10 kHz | | 21 | | |
| $E_N$ | Input voltage noise | All PS and NS packages; All TL07xM devices | $R_S$ = 20 Ω, f = 10 Hz to 10 kHz | | 4 | | $µV_{RMS}$ |
| | | All other devices | f = 0.1 Hz to 10 Hz | | 1.4 | | $µV_{RMS}$ |
| $I_N$ | Input current noise | $R_S$ = 20 Ω, f = 1 kHz | | | 10 | | fA/√Hz |
| | Phase margin | TL07xC, TL07xAC, TL07xBC, TL07xI | G = +1, $R_L$ = 10 kΩ, $C_L$ = 20 pF | | 56 | | ° |
| | Overload recovery time | $V_{IN}$ X gain > $V_S$ | | | 300 | | ns |
| THD+N | Total harmonic distortion + noise | All PS and NS packages; All TL07xM devices | $V_O$ = 6 $V_{RMS}$, $R_L$ ≥ 2 kΩ, f = 1 kHz, G = +1, $R_S$ ≤ 1 kΩ | | 0.003 | | % |
| | | All other devices | $V_S$ = 40 V, $V_O$ = 6 $V_{RMS}$, G = +1, f = 1 kHz | | 0.00012 | | % |
| EMIRR | EMI rejection ratio | TL07xC, TL07xAC, TL07xBC, TL07xI | f = 1 GHz | | 53 | | dB |
| $Z_O$ | Open-loop output impedance | TL07xC, TL07xAC, TL07xBC, TL07xI | f = 1 MHz, $I_O$ = 0 A | | 125 | | Ω |

# IC Pin Configuration of TL074:



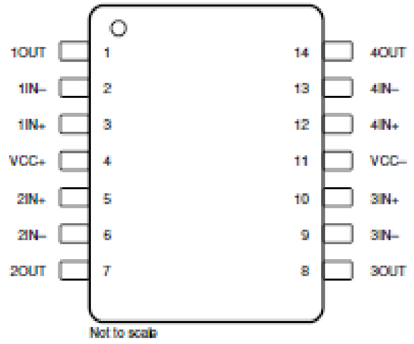



**Figure 5-8. TL074x D, N, NS, PW, J, DYY, and W Package, 14-Pin SOIC, PDIP, SO, TSSOP, CDIP, SOT-23, and CFP (Top View)**

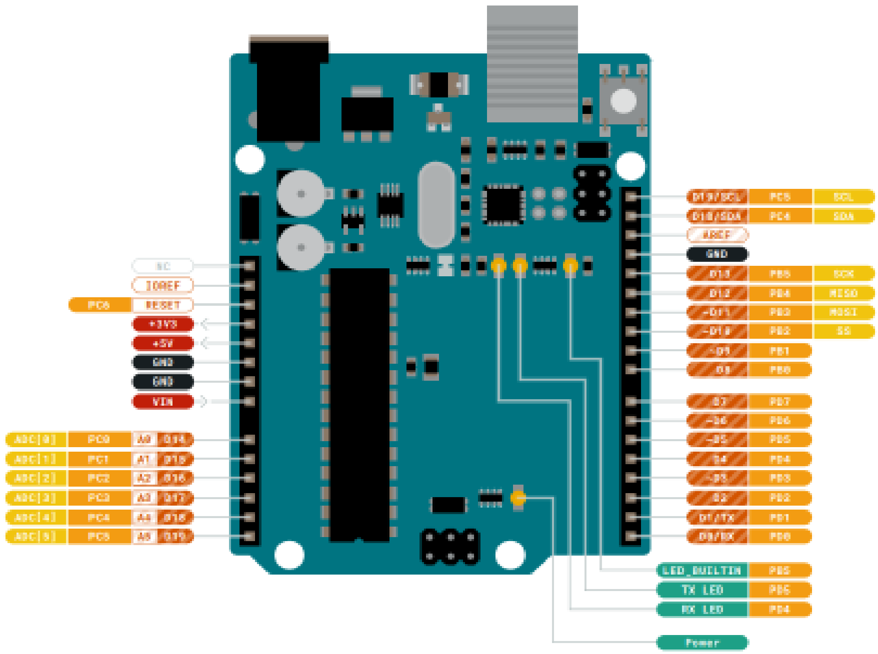
**Table 5-6. Pin Functions: TL074x**

| PIN | | I/O | DESCRIPTION |
|---|---|---|---|
| NAME | NO. | | |
| 1IN– | 2 | I | Inverting input |
| 1IN+ | 3 | I | Noninverting input |
| 1OUT | 1 | O | Output |
| 2IN– | 6 | I | Inverting input |
| 2IN+ | 5 | I | Noninverting input |
| 2OUT | 7 | O | Output |
| 3IN– | 9 | I | Inverting input |
| 3IN+ | 10 | I | Noninverting input |
| 3OUT | 8 | O | Output |
| 4IN– | 13 | I | Inverting input |
| 4IN+ | 12 | I | Noninverting input |
| 4OUT | 14 | O | Output |
| $V_{CC-}$ | 11 | — | Power supply |
| $V_{CC+}$ | 4 | — | Power supply |

# IC Pin Configuration of Arduino UNO:

Arduino® UNO R3

5 Connector Pinouts




*Pinout*

8 / 13 Arduino® UNO R3 Modified: 31/03/2023

### 5.1 JANALOG

| Pin | Function | Type | Description |
|---|---|---|---|
| 1 | NC | NC | Not connected |
| 2 | IOREF | IOREF | Reference for digital logic V - connected to 5V |
| 3 | Reset | Reset | Reset |
| 4 | +3V3 | Power | +3V3 Power Rail |
| 5 | +5V | Power | +5V Power Rail |
| 6 | GND | Power | Ground |
| 7 | GND | Power | Ground |
| 8 | VIN | Power | Voltage Input |
| 9 | A0 | Analog/GPIO | Analog input 0 /GPIO |
| 10 | A1 | Analog/GPIO | Analog input 1 /GPIO |
| 11 | A2 | Analog/GPIO | Analog input 2 /GPIO |
| 12 | A3 | Analog/GPIO | Analog input 3 /GPIO |
| 13 | A4/SDA | Analog input/I2C | Analog input 4/I2C Data line |
| 14 | A5/SCL | Analog input/I2C | Analog input 5/I2C Clock line |

### 5.2 JDIGITAL

| Pin | Function | Type | Description |
|---|---|---|---|
| 1 | D0 | Digital/GPIO | Digital pin 0/GPIO |
| 2 | D1 | Digital/GPIO | Digital pin 1/GPIO |
| 3 | D2 | Digital/GPIO | Digital pin 2/GPIO |
| 4 | D3 | Digital/GPIO | Digital pin 3/GPIO |
| 5 | D4 | Digital/GPIO | Digital pin 4/GPIO |
| 6 | D5 | Digital/GPIO | Digital pin 5/GPIO |
| 7 | D6 | Digital/GPIO | Digital pin 6/GPIO |
| 8 | D7 | Digital/GPIO | Digital pin 7/GPIO |
| 9 | D8 | Digital/GPIO | Digital pin 8/GPIO |
| 10 | D9 | Digital/GPIO | Digital pin 9/GPIO |
| 11 | SS | Digital | SPI Chip Select |
| 12 | MOSI | Digital | SPI1 Main Out Secondary In |
| 13 | MISO | Digital | SPI Main In Secondary Out |
| 14 | SCK | Digital | SPI serial clock output |
| 15 | GND | Power | Ground |
| 16 | AREF | Digital | Analog reference voltage |
| 17 | A4/SD4 | Digital | Analog input 4/I2C Data line (duplicated) |
| 18 | A5/SD5 | Digital | Analog input 5/I2C Clock line (duplicated) |

# Software descriptions

1. **MATLAB**: MATLAB is a high-level programming language and development environment that is widely used for numerical computation, algorithm development, and data analysis. It provides a vast array of built-in functions and toolboxes for mathematical operations, signal processing, image analysis, control systems, and more. MATLAB's intuitive syntax and interactive environment make it a powerful tool for scientific and engineering applications.
2. **Spike Recorder**: Spike Recorder is a software application designed for neuroscience research and analysis. It is used to record, visualize, and analyze neural activity, particularly spike trains generated by neurons. Spike Recorder offers features such as data acquisition, spike sorting, event detection, and visualization tools, enabling researchers to study and interpret neuronal firing patterns.
3. **Multisim**: Multisim is a powerful software tool used for circuit design, simulation, and analysis. It allows users to create and simulate electronic circuits using a wide range of components and instruments. Multisim provides a comprehensive set of simulation capabilities, including time-domain and frequency-domain analysis, virtual instrumentation, and interactive circuit debugging, making it a popular choice for electrical and electronic engineers.
4. **Arduino C**: Arduino C is a programming language specifically tailored for programming Arduino microcontrollers. It is based on the C programming language but includes additional libraries and functions that simplify the process of interacting with Arduino hardware. Arduino C allows users to control inputs and outputs, interface with sensors and actuators, and create interactive projects using Arduino boards.
5. **Python**: Python is a versatile, general-purpose programming language known for its simplicity and readability. It offers a wide range of libraries and frameworks for various applications, including data analysis, web development, machine learning, and more. Python's rich ecosystem, ease of use, and powerful libraries like NumPy, Pandas, and Matplotlib make it a popular choice among developers for diverse projects and tasks.

# Hardware descriptions

1. **TL074 Operational Amplifier**: The TL074 is an operational amplifier (op-amp) integrated circuit that is widely used in electronic circuits. It is a quad op-amp, meaning it contains four individual op-amps in a single package. The TL074 is known for its high input impedance, low noise, and wide bandwidth, making it suitable for various applications such as audio amplification, signal conditioning, and voltage amplification.

2. **Arduino Uno**: Arduino Uno is a popular microcontroller board based on the Atmel ATmega328P microcontroller. It serves as the core component of many electronic projects and provides a simple and accessible platform for prototyping and building interactive systems. The Arduino Uno board features digital input/output pins, analog input pins, serial communication interfaces, and other peripheral connections, making it versatile for a wide range of applications and projects.

3. **Resistors, Capacitors**: Resistors and capacitors are fundamental passive electronic components used in almost all electronic circuits. Resistors are used to control the flow of electric current and create specific voltage drops, while capacitors store and release electrical charge. They are essential for tasks such as voltage division, current limiting, signal filtering, timing, and coupling in various electronic systems and circuits.

4. **Gel Electrodes**: Gel electrodes are specialized electrodes used in biomedical applications, particularly in electroencephalography (EEG) and electromyography (EMG). These electrodes feature a gel-filled cavity that enhances the conductivity between the electrode and the skin. Gel electrodes are non-invasive and provide stable and reliable electrical connections for measuring bioelectric signals from the human body, making them suitable for medical diagnostics and research purposes.

5. **PCB**: A PCB, or Printed Circuit Board, is a physical hardware component used in electronics. It provides a platform for mounting and interconnecting electronic components to create functional circuits. A PCB consists of a non-conductive substrate made of materials like fiberglass-reinforced epoxy. Conducting layers made of copper are etched or deposited onto the substrate to form traces and pads.

Components are mounted onto the PCB using soldering techniques, and the traces on the PCB connect the components, allowing for the flow of electrical signals and power. PCBs can be single-sided or multi-layered, with advanced techniques like surface mount technology enabling smaller component placement. PCBs provide a reliable platform for assembling electronic circuits found in various devices.

# Certificates Recognitions

**Certificate of participation for Paper Publication in International Conference on Advances in Engineering and Technology for Intelligent Systems**

Dayananda Sagar College of Engineering

Shavige Malleshwara Hills, Kumaraswamy Layout, Bengaluru - 560 111. Karnataka, India.
An Autonomous Institute affiliated to Visvesvaraya Technological University (VTU),
Approved by AICTE and UGC, Accredited by NAAC with "A" grade

Department of Electronics and Telecommunication Engineering
(Accredited by NBA: 2022-2024)

International Conference on Advances in Engineering and Technology for Intelligent Systems

ICAETIS-2023

May 16th - 18th, 2023

Certificate of Participation

*This is to Certify that* Vidyashree K N, SrikaraBharadwaj K S, Sirish Hublikar, Sohan Gowda R, Sai Sarthak S

*of* Dayananda Sagar College of Engineering, Bengaluru

*has presented a paper at ICAETIS - 2023, held during 16th - 18th May 2023, organized by Department of Electronics and Telecommunication Engineering, DSCE, Bangalore.*

Dr. Anju V Kulkarni
Convenor/Organizing chair, ICAETIS – 2023
HOD and Professor, Dept of ETE
DSCE, Bangalore - 560111

Dr. B G Prasad
Principal
DSCE, Bangalore – 560111

**Course certificate for Machine learning in Python and R in Data Science**


Certificate no: UC-22c5bee3-0944-4780-a12d-45b2451f8178
Certificate url: ude.my/UC-22c5bee3-0944-4780-a12d-45b2451f8178
Reference Number: 0004

CERTIFICATE OF COMPLETION

# Machine Learning A-Z™: Python & R in Data Science [2022]

Instructors **Kirill Eremenko, Hadelin de Ponteves, Ligency I Team, Ligency Team**

## Sirish Hublikar

Date **Dec. 2, 2022**
Length **43 total hours**

**Course certificate for Machine learning in python**


COURSE CERTIFICATE

Mar 24, 2023

SRIKARA BHARADWAJ K S

has successfully completed

Machine Learning with Python

an online non-credit course authorized by IBM Skills Network and offered through Coursera

EDUCATION FOR EVERYONE coursera COURSE CERTIFICATE

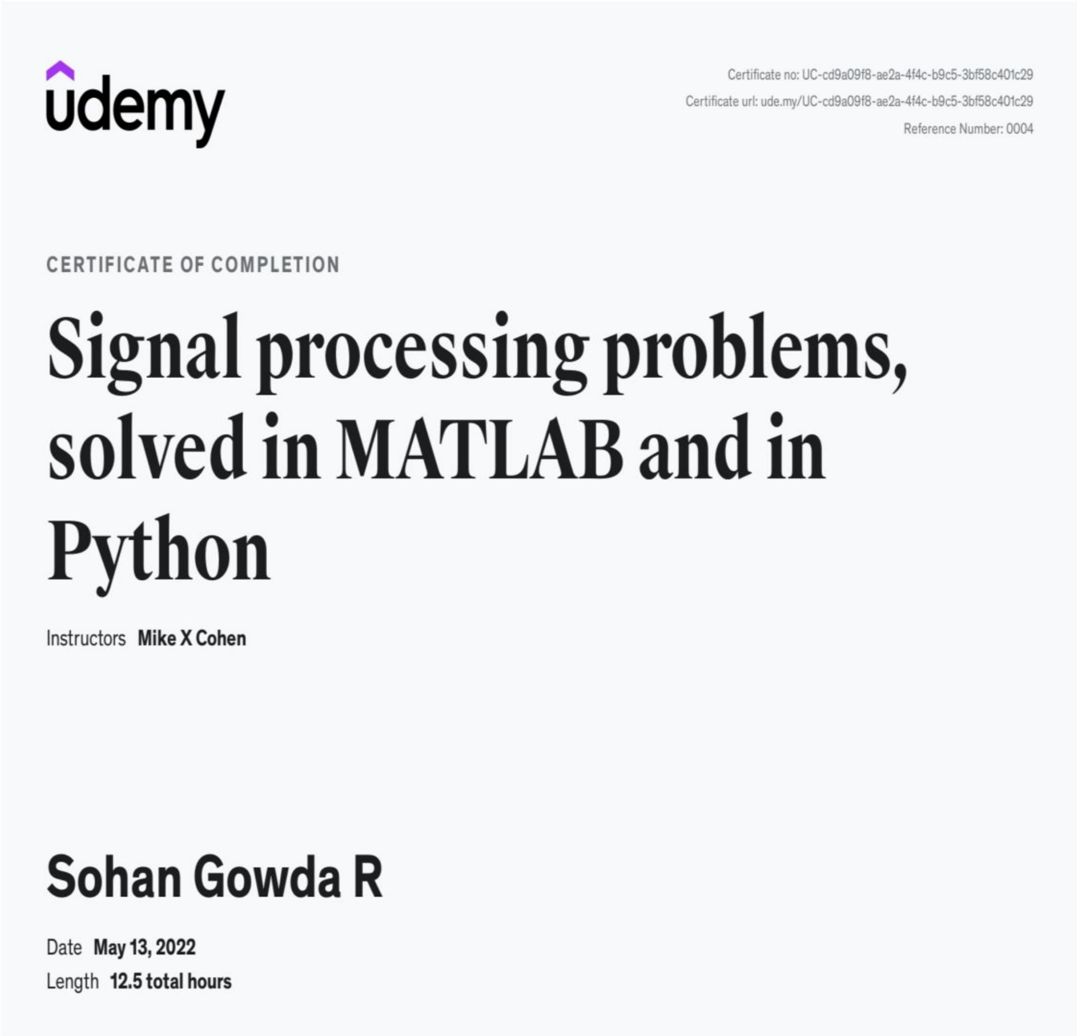
Saeed Aghabozorgi
Sr. Data Scientist
IBM

Joseph Santarcangelo
Senior Data Scientist
IBM

Verify at:
https://coursera.org/verify/48ZUJDBR46AH

Coursera has confirmed the identity of this individual and their participation in the course.

**Course certificate for Signal processing problems in MATLAB and python**



udemy

Certificate no: UC-cd9a09f8-ae2a-4f4c-b9c5-3bf58c401c29
Certificate url: ude.my/UC-cd9a09f8-ae2a-4f4c-b9c5-3bf58c401c29
Reference Number: 0004

CERTIFICATE OF COMPLETION

# Signal processing problems, solved in MATLAB and in Python

Instructors **Mike X Cohen**

**Sohan Gowda R**

Date **May 13, 2022**
Length **12.5 total hours**

# Hard copy of the presented conference paper

# Multi-Signal Acquisition System for Bio-Signals

Vidyashree K N
*Dept. of Electronics & Communication Engg.*
*Dayananda Sagar College of Engineering*
Bengaluru, India
vidyashree-ece@dayanandasagar.edu

Srikara Bharadwaj K S
*Dept. of Electronics & Communication Engg.*
*Dayananda Sagar College of Engineering*
Bengaluru, India
srikar.bharadwaj274@gmail.com

Sirish Hublikar
*Dept. of Electronics & Communication Engg*
*Dayananda Sagar College of Engineering*
Bengaluru, India
sirishhublikar123@gmail.com

Sohan Gowda R
*Dept. of Electronics & Communication Engg*
*Dayananda Sagar College of Engineering*
Bengaluru, India
sohanqw@gmail.com

Sai Sarthak S
*Dept. of Electronics & Communication Engg*
*Dayananda Sagar College of Engineering*
Bengaluru, India
saisarthak561@gmail.com

***Abstract*— In the field of human health care, it is important to have a health monitoring system in place. Health monitoring contributes to a wide variety of applications such as hospitals, home care units, sports training, and emergency monitoring systems. In this work, a wireless bio signal system is designed for extracting and monitoring ECG, EEG and EMG. Dry electrodes, bio signal amplifiers and filters are used for the development of this system. Due to its low cost and portability, this prototype is also suitable for students and researchers who may not have access to more expensive ECG, EEG, or EMG machines. The ultimate goal of this project is to implement a low cost, highly efficient system for extraction of bio signals.**

***Keywords—Health Monitoring, bio signal amplifier, filters***

## I. INTRODUCTION

A bio signal is, by definition, an electrical signal emanating from a living organism. A bio signal is generated by our body when we flex a muscle, move our eyes, think, or sleep.

Electroencephalography (EEG) is a measurement of potentials that reflect the electrical activity of the human brain. It is a readily available test that provides evidence of how the brain functions over time. Medical professionals and researchers frequently utilise the EEG to examine brain activity and identify neurological problems. One of the most important tools for diagnosing neurological diseases, such as epilepsy, brain tumours, head injury, sleep disorders, dementia, and monitoring the depth of anaesthesia during surgery, is the study of the brain's electrical activity via EEG records. It is also helpful for the treatment of abnormalities, behavioural disturbances (e.g., Autism), attention disorders, learning problems and language delay. Frequency is one of the most important criteria for assessing abnormalities in clinical EEGs and for understanding functional behaviours in cognitive research. Frequency refers to rhythmic repetitive activity (in Hz). The number of cycles in second is counted as frequency. With billions of oscillating communities of neurons as its source, human EEG potentials are manifested as aperiodic unpredictable oscillations with intermittent bursts of oscillations. In healthy adults, the amplitudes and frequencies of such signals change from one state to another, such as wakefulness and sleep. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies, respectively, are typically categorized in specific bands such as 0.5–4 Hz (delta, d), 4–8 Hz (Theta, h), 8–13 Hz (alpha, a), 13–30 Hz (beta, b) and >30 Hz (gamma, c). Higher frequencies are often more common in abnormal brain states such as epilepsy.

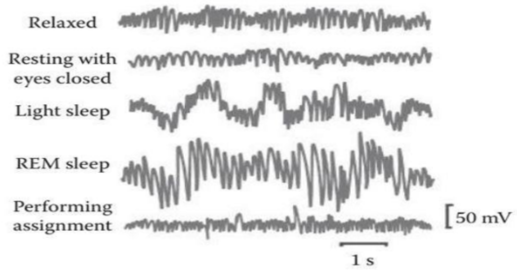



Fig 1. Various sleep stages as represented in the EEG in comparison with the EEG of a person solving an assignment as an event-related high-frequency potential.

The electrocardiogram (ECG) is a useful tool for studying the heart's functional and structural status. ECG is a recording of the bioelectrical potentials generated on the surface of the body by the heart. In 1901, Willem Einthoven used a string galvanometer to measure ECG and assigned letters P, Q, R, S and T to the various deflections(Fig 2.).In recent years, an automated method of analysing ECG signals using real-time processing has become increasingly important for accurately diagnosing cardiac diseases. In a typical ECG tracing of the cardiac cycle (heartbeat) most of the energy is concentrated in QRS complex and very little energy in T wave and U wave, which is normally invisible in 50 to 75 % of ECGs because it is hidden by the T wave and upcoming new P wave. The type of wave and the action which causes them are summarized the flat horizontal segments, PR segment and the segment between TP segments constitute the baseline of the electrocardiogram. In a normal healthy heart, the baseline is equivalent to the isoelectric line (0mV). However, in a diseased heart the baseline may be elevated (e.g., cardiac ischemia) or depressed (e.g., myocardial infarction) relative to the isoelectric line due to flow of injury currents during the conduction periods of the TP and PR intervals when the ventricles are at rest. Normally the baseline drift caused by patient breathing, 50/60 Hz power line interference, bad electrodes and improper positioning of electrodes will corrupt ECG signal severely and makes the detection of QRS complexes very difficult or may even lead to give false detection. Many researchers developed various procedures and algorithms to detect QRS complexes accurately and precisely.

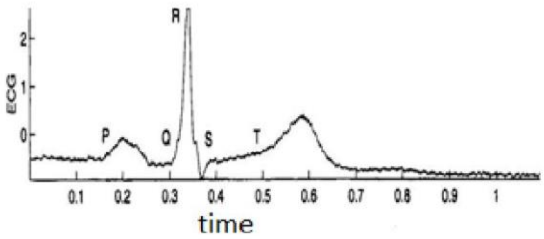



Fig 2. Standard ECG of a normal person.

Electromyography (EMG) is the study of the electrical activity of the muscle and is a valuable tool in the assessment of neuromuscular disorders. EMG findings are used to detect and describe various disease processes affecting the Motor Unit (MU), the muscle's smallest functional unit. There are numerous neuromuscular disorders that influence the spinal cord, nerves or muscles. Early finding and diagnosis of these diseases by clinical examination and laboratory tests are crucial for their management as well as their anticipation through prenatal diagnosis and genetic counselling. This information is also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases. The purpose of clinical electromyography (EMG) is to analyse the electrical activity from skeletal muscles during rest and during weak and maximal contraction. EMG signal is composed of motor unit action potentials (MUAPs)which is a compound signal generated by the muscle fibres of the MU, and its amplitude, duration, and shape vary in individual muscles according to the number of factors including the number of muscle fibres of the MU, the spatial distribution of endplates and the age of the subject. Furthermore, the individual muscle MUAPs vary, and it is insufficient to evaluate a single or a few MUAPs. Thus, MUAPs can be identified and tracked using pattern recognition techniques. The resulting information can be used to determine the origin of the disease, i.e., neuropathic or myopathic. When a patient maintains a low level of muscle contraction, individual MUAPs can be easily recognized, since only a few MUs are active. As contraction intensity increases, more MUs are recruited; different MUAPs overlap, causing an interference pattern (i.e., superimposed MUAPs) EMG signal decomposition and MUAP classification into groups of similar shapes give significant information for the assessment of neuromuscular pathology. Recent advancements in computer technology have enabled automated EMG analysis. Many computer-based quantitative EMG analysis algorithms are commercially available or developed, but none of them are broadly accepted for widespread routine clinical use.

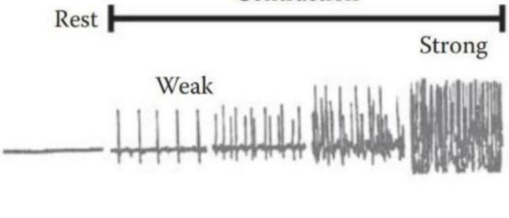



Fig 3.EMG waveform while contracting and relaxation of muscles

Bio signals can be measured using sensors such as electrodes that are skin surface transducers. Transducers are a device which converts one form of physical signal into an electric signal. The signal can be processed in electric circuits, that are bio electrodes, which are commonly used for measuring bio signals. In this proposed method, electrodes made up of silver-silver chloride metal are used. Among the Bio Signal measuring devices well known devices are electrocardiogram (ECG), electroencephalogram (EEG) and electromyogram (EMG). These signals are mainly used for applications like disease diagnosis. ECG signals are bipolar low frequency signals. The normal range of ECG signal is 0.05-100Hz having its amplitude range from 10 microvolt to 5 millivolts. 1mv is typical value for ECG amplitude. For EEG signal at low frequency 0.5-100Hz, 1-100 microvolt peak to peak is voltage range at cranial surface. ECG signal voltage is 100 times greater than EEG signal. So, EEG signal requires input preamplifier with high gain. It is more complex than ECG. In this proposed methodology the aim is to develop a low-cost Bio Signal acquisition system which is affordable for the people of developing and underdeveloped countries. In previous papers, separate devices were used for ECG, EEG, and EMG. This paper presents a Bio Signal acquisition system, which is portable and battery powered.

## II. LITERATURE REVIEW

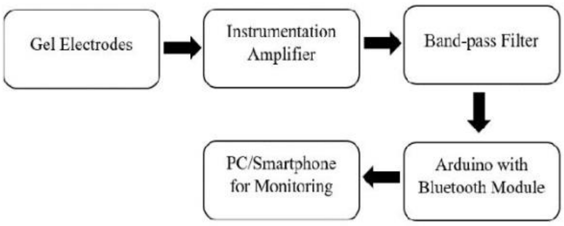
Nasir Faruk et al.[2] have provided a thorough summary of ECG monitoring devices. It is challenging for academics and medical professionals in underdeveloped nations to access these gadgets due to their complexity. The price of the equipment makes it nearly hard for hospitals in rural regions to afford, which is another cause for concern. It was concluded that the majority of the studied devices had a constrained range of diagnosis, were unable to develop a dual ECG data transfer system, and were unable to move towards real-time commercialization. Moreover, there were no more than three leads for the ECG collection devices, and the power usage and consumption were not flexible, i.e., there were no dual power supply sources used (i.e.an AC and DC). In addition, smart cloud-based systems for device remote monitoring with location features were not available in many devices.

Danilo Ricciardi et al[3], have investigated the impact of 40 Hz compared to 150 Hz high-frequency cut-offs on ECG quality and clinical interpretation in a single-centre surgical outpatient population. In a low-risk group, using a 40 Hz high-frequency cut-off for bandpass filtering may be appropriate and result in higher tracing quality without having a substantial impact on clinical ECG interpretation.

Ms. Nyni K.A et al[5], have designed a wireless bio signal health monitoring which integrates both the extracting and monitoring of the Bio Signal such as ECG, EEG and EMG. The developed integrating system is utilised for wirelessly monitoring patient biopotential variations in their heart, neuronal activity of the brain, and body muscles. The wired health monitoring system's drawbacks are somewhat solved by the effective installation of this wireless technology.

## III. BLOCK DIAGRAM

Fig 4. Block Diagram




The proposed prototype uses three electrodes to acquire the bio signals. The electrode placement for ECG, EEG and EMG is given below.

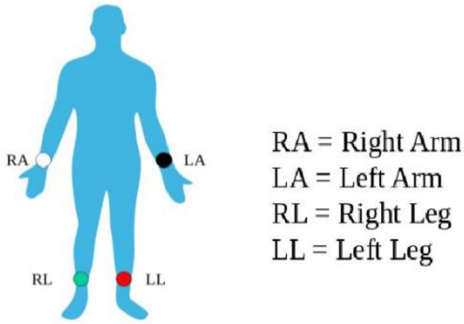



Fig 5. Gel electrode placement for ECG

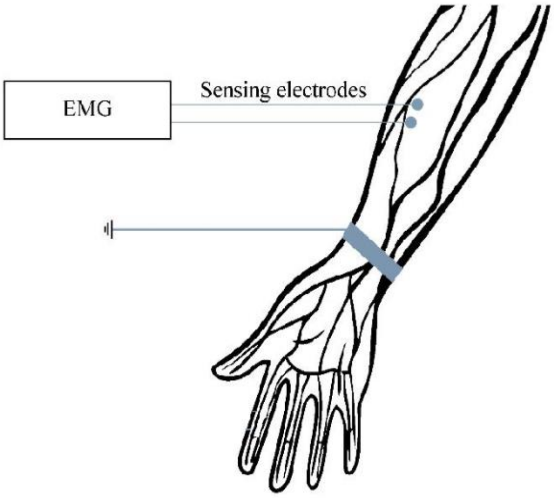



Fig 6. Gel electrode placement for EMG

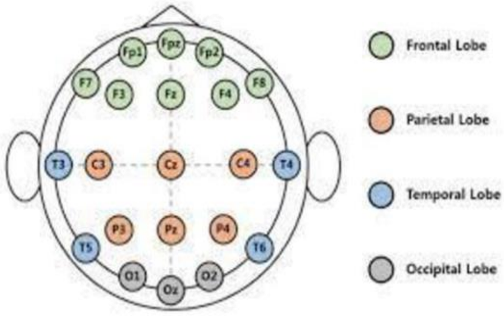



Fig 7. Gel electrode placement for EEG

## IV. IMPLEMENTATION PROCESS

### A. *Gel Electrodes*

Gel electrodes are used in acquiring the signals from the skin. These electrodes use a gel to carry an electric current from the skin to a measuring instrument. Gel acts as a conductor to carry current. A sticky patch may hold the gel electrode on the skin so that the electrical activity of the heart or brain or muscle can be measured. The electrodes are connected to a clipper which is attached to the circuit. The electrodes are placed in different positions for acquiring particular signal. Three electrodes are used to acquire the signals. For ECG signal the electrodes are place as shown in Fig 5. The electrodes are placed on right and left wrist which is the main source for signal. Another electrode is placed on the right leg which acts as the amplifier reference. Right leg is chosen as it is away from the heart.

For EMG the electrodes are placed as shown in the Fig 6. The two electrodes are placed on the muscle and the other electrode is the amplitude reference.

For EEG the figure(Fig 7.) depicts the 10-20 electrode position format. The electrodes are place as per the signal required. Two electrodes are used for the signal acquisition and the third electrode acts as the amplitude reference.

### B. *Instrumentation Amplifier*

Instrumentation amplifiers are differential amplifiers fitted with input buffer amplifiers, which eliminate the need for input impedance matching, making them particularly useful for measurement and test equipment. Texas Instruments' TL074 quad low-noise JFET-input general-purpose operational amplifier is the key component of the design. The quad implies that there are four individual operational amplifiers. TL074 is a low noise FET the reason for its wide usage in bio medical signal acquisitions.

The instrumentation amplifier circuit design used is modified compared to standard design to suit the required applications. An amplifier reference maintains the idle output voltage at a half-level (midpoint) is given as input. The signals from the electrodes are the other inputs to the instrumentation amplifier. Overall, a gain of about 10 is provided by the instrumentation amplifier by the combination of passive components.

*C. Bandpass Filter*

The output from the instrumentation amplifier is given as an input to bandpass filter which limits the unwanted signals from passing through. The filter values are selected so as to be able to acquire all biomedical signals without additional filtering. The overall gain of the bandpass filter is about 1000 times. Very high gain is needed as the biomedical signals have very less amplitude. The high CMRR value of TL074 is very useful in removal of noise from the circuit. The passband range is kept very low for better quality signal.

*D. Driven Right Leg (DRL)*

The third electrode is used in the driven right leg circuit. They are used to provide the amplitude reference voltage which is given to the instrumentation amplifier. A reference voltage is provided to the TL074 which is obtained using the voltage divider circuit. The driven right leg circuit is used in eliminating the common mode voltages from the signals of two electrodes. As the bio signals are measured in millivolts or in microvolts they are very sensitive to any sort of interference. The driven right leg circuit also helps in eliminating the interference of 50Hz caused by the supply. Basically, the Driven right leg signal is feedback to the body nullifying the unwanted signal. Generally the DRL is connected away from the two electrodes.

Arduino UNO is connected to the output of the circuit. Arduino is used to convert the analog signal obtained from the circuit to the digital signal. This signal is plotted on the serial plotter using the Arduino application on the PC/Laptop. Better filtering can be applied to the signal on MATLAB. The signals are recorded as audio signals using the Backyard Brain software and provided to the MATLAB.

## V. RESULTS

After the signal is passed through Arduino, it is saved and loaded into MATLAB for better visualization and further filtering to get a much better, cleaner looking signal which can be used in many applications. The ECG Signal is shown below.

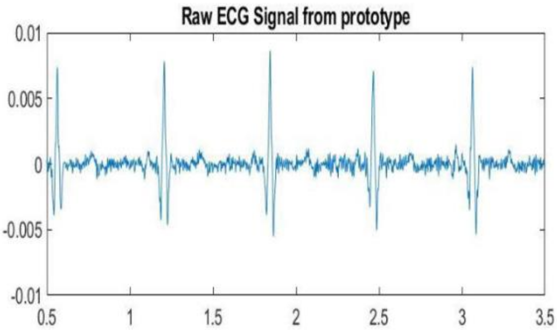



Fig 8. Raw ECG Signal from device

The ECG signal was measured by placing the three electrodes on Right Arm, Left Arm and Right Leg. As the ECG waveform in Fig 8 shows there is high frequency noise since the circuit was on breadboard. To get a cleaner waveform, a Butterworth low pass filter can be applied with a cutoff frequency of 40 Hz [3]. Signal to Noise ratio(SNR) of the ECG signal was calculated and was obtained at about 20dB. Noise was obtained by difference of the original signal to the filtered signal and SNR was calculated using the Root Mean Square(RMS) value of the filtered and noise signal.

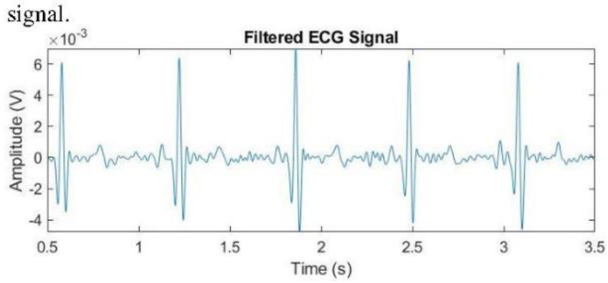



Fig 9. Filtered ECG Signal

The EEG Waveform is shown below.

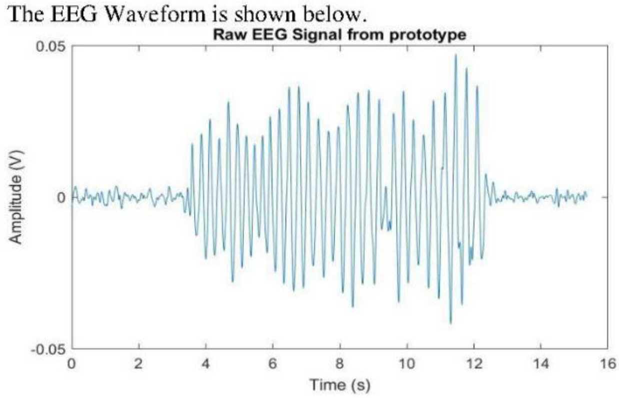



Fig 10. Raw EEG Signal (Alpha wave) from device

The EEG signal was taken during movement of hands which produces alpha waves. The electrodes were placed behind the ears and the DRL electrode was placed at the back of the neck. As can be seen from the Fig. 10 there is lot of interference. Hence it is passed through a low Butterworth low pass filter of cutoff 20 Hz. The output of the filter is shown below. Signal to Noise ratio (SNR) of the EEG signal was calculated and was obtained at about 20dB. Noise was obtained by difference of the original signal to the filtered signal and SNR was calculated using the Root Mean Square (RMS) value of the filtered and noise signal.

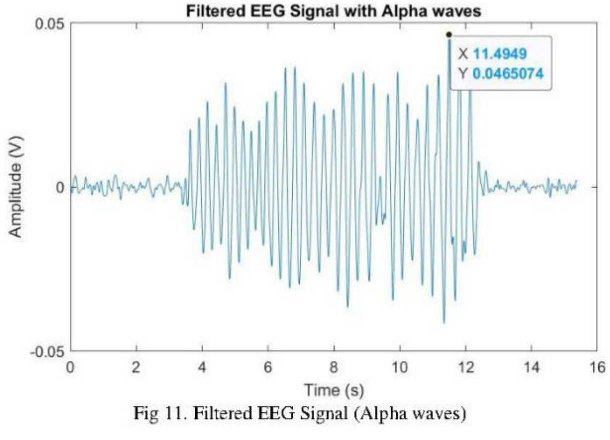



Fig 11. Filtered EEG Signal (Alpha waves)

Next, the EMG signal was recorded during the movement of hands. The electrodes were placed on the muscles of the left arm and the DRL electrode was placed at the back of the palm. Compression of the bicep would generate the EMG signal; the low amplitude signal in the image shows the hand in the rest or relaxed state. The quality of the EMG signal can be justified by the image as it shows the compression and relaxation of the muscles by the arm.

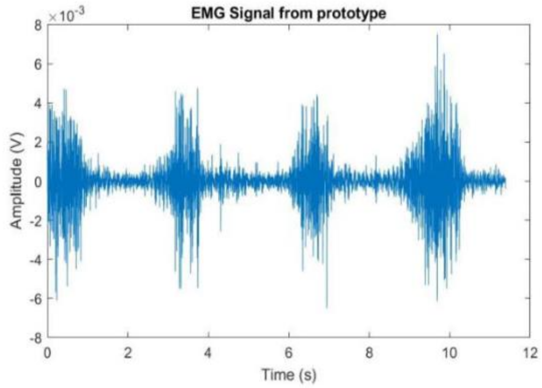


Fig 12. EMG Signal from device

## VI. CONCLUSION

A prototype was developed which is able to acquire ECG, EEG and EMG signal. The extracted signal was amplified and filtered to obtain the desired output. The SNR value obtained is practical and acceptable for any bio-medical signal related applications. The quality of the signal can be improved with further filtering the signal. Further the signal can be utilized for research purposes. The signal can also be filtered as per requirements. The device also can be used in various applications using the signals. This design develops a simple and faster health monitoring system with low cost and high efficiency settings.

## REFERENCES


[1] D. Saptono, B. Wahyudi, and B. Irawan, "Design of EEG signal acquisition system using Arduino MEGA1280 and EEGAnalyzer," *MATEC Web of Conferences*, vol. 75, p. 04003, 2016.

[2] Nasir Faruk, Abubakar Abdulkarim, Ifada Emmanuel, Yusuf Y. Folawiyo, Kayode S. Adewole, Hammed A. Mojeed, Abdukareem A. Oloyede, Lukman A. Olawoyin, Ismaeel A. Sikiru, Musa Nehemiah, Abdulsalam Ya'u Gital, Haruna Chiroma, James A. Ogunmodede, Mubarak Almutairi, Ibraheem A. Katibi, "A comprehensive survey on low-cost ECG acquisition systems: Advances on design specifications, challenges and future direction", Elsevier Biocybernetics and Biomedical Engineering, Volume 41, Issue 2, pp. 474-502, June 2021.

[3] Danilo Ricciardi, Ilaria Cavallari, Antonio Creta, Giacomo Di Giovanni, Vito Calabrese, Natale Di Belardino, Simona Mega, Iginio Colaiori, Laura Ragni, Claudio Proscia, Antonio Nenna, Germano Di Sciascio, "Impact of the high-frequency cutoff of bandpass filtering on ECG quality and clinical interpretation: A comparison between 40 Hz and 150 Hz cutoff in a surgical preoperative adult outpatient population", Elsevier Journal of Electro cardiology, Volume 49, Issue 5, 691-695, October 2016.

[4] Jiawei Xu, Srinjoy Mitra, Chris Van Hoof, Refet Firat Yazicioglu, Kofi A. A. Makinwa, "Active Electrodes for Wearable EEG Acquisition: Review and Electronics Design Methodology", IEEE Reviews in Biomedical Engineering, Volume 10, pp. 187-198, January 2019.

[5] Ms. Nyni K.A, Linson K Vincent, Lisiya Varghese, Liya V.L, Neethu Johny A, Yesudas C. V, "Wireless Health Monitoring System for ECG, EMG and EEG Detecting", 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 17 March 2017.

[6] David Alejandro Fernandez Guzman, Stefano Sapienza, Bianca Sereni, Paolo Motto Ros, "Very low power event-based surface EMG acquisition system with off-the-shelf components", IEEE Biomedical Circuits and Systems Conference (BioCAS), October 2020.

[7] R. Martinek, M. Ladrova, M. Sidikova, R. Jaros, K. Behbehani, R. Kahankova, and A. Kawala-Sterniuk, "Advanced bioelectrical signal processing methods: Past, present, and future approach—part III: Other biosignals," *Sensors*, vol. 21, no. 18, p. 6064, 2021.

[8] G. Yang, Z. Sun, Z. Wang, and G. Sun, "Detection and identification the human surface ELECTROMYOGRA signal," *IOP Conference Series: Earth and Environmental Science*, vol. 440, no. 2, p. 022016, 2020.

# Plagiarism Report

# Multi Signal Acquisition For Health Monitoring

# Multi Signal Acquisition For Health Monitoring

ORIGINALITY REPORT

| 20% | 15% | 15% | 11% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | www.ijeee.net<br>Internet Source | 3% |
| 2 | ijettjournal.org<br>Internet Source | 3% |
| 3 | ijarcce.com<br>Internet Source | 2% |
| 4 | Submitted to BMS College of Engineering<br>Student Paper | 2% |
| 5 | Siuly Siuly, Yan Li, Yanchun Zhang. "EEG Signal Analysis and Classification", Springer Nature, 2016<br>Publication | 1% |
| 6 | repository.sustech.edu<br>Internet Source | 1% |
| 7 | Submitted to Engineers Australia<br>Student Paper | 1% |
| 8 | IFMBE Proceedings, 2009.<br>Publication | 1% |

| | | |
|---|---|---|
| 9 | "6th International Conference on the Development of Biomedical Engineering in Vietnam (BME6)", Springer Science and Business Media LLC, 2018<br>Publication | 1 % |
| 10 | www.researchgate.net<br>Internet Source | <1 % |
| 11 | IFMBE Proceedings, 2013.<br>Publication | <1 % |
| 12 | ijrar.com<br>Internet Source | <1 % |
| 13 | www.ijarse.com<br>Internet Source | <1 % |
| 14 | Submitted to University of Bradford<br>Student Paper | <1 % |
| 15 | eprints.usq.edu.au<br>Internet Source | <1 % |
| 16 | ijarcsse.com<br>Internet Source | <1 % |
| 17 | Submitted to University of East London<br>Student Paper | <1 % |
| 18 | mantechpublications.com<br>Internet Source | <1 % |

| | | |
|---|---|---|
| 19 | Karunakaran, S.. "Changes in network dynamics during status epilepticus", Experimental Neurology, 201204<br>Publication | <1 % |
| 20 | Submitted to City University<br>Student Paper | <1 % |
| 21 | Sunil Kumar, Kashyap Kambhatla, Fei Hu, Mark Lifson, Yang Xiao. "Ubiquitous Computing for Remote Cardiac Patient Monitoring: A Survey", International Journal of Telemedicine and Applications, 2008<br>Publication | <1 % |
| 22 | link.springer.com<br>Internet Source | <1 % |
| 23 | Submitted to West Lothian College<br>Student Paper | <1 % |
| 24 | patents.google.com<br>Internet Source | <1 % |
| 25 | www-dev.cldnet.analog.com<br>Internet Source | <1 % |
| 26 | www.annualreports.com<br>Internet Source | <1 % |
| 27 | mafiadoc.com<br>Internet Source | <1 % |

| | | |
|---|---|---|
| 28 | Chandrasiri, M. E., R. M. T. M. Dhanapala, W. G. K. G. Kumari, and R. Ranaweera. "PC based Electroencephalogram system", 2013 IEEE 8th International Conference on Industrial and Information Systems, 2013.<br>Publication | <1 % |
| 29 | Intelligent Systems Reference Library, 2015.<br>Publication | <1 % |
| 30 | Ladan Eskandarian, Merwa Al-Rasheed, Jean Paul Ilogon, Amirali Toossi, Hani E. Naguib. "Multidimensional evaluation of highly durable scalable and seamlessly integrated fiber-based electrodes for wearable applications", Applied Materials Today, 2023<br>Publication | <1 % |
| 31 | Patidar, Shivnarayan, Ram Bilas Pachori, and Niranjan Garg. "Automatic diagnosis of septal defects based on tunable-Q wavelet transform of cardiac sound signals", Expert Systems with Applications, 2015.<br>Publication | <1 % |
| 32 | archive.org<br>Internet Source | <1 % |
| 33 | en.wikipedia.org<br>Internet Source | <1 % |
| 34 | ethesis.nitrkl.ac.in<br>Internet Source | <1 % |

| | | |
|---|---|---|
| 35 | lib.buet.ac.bd:8080<br>Internet Source | <1% |
| 36 | www.codeproject.com<br>Internet Source | <1% |
| 37 | "Digital Human Modeling and Applications in Health, Safety, Ergonomics, and Risk Management. Healthcare and Safety of the Environment and Transport", Springer Science and Business Media LLC, 2013<br>Publication | <1% |
| 38 | Dmitry Kuleshov, Daniil Morozov, Victoria Shiryaeva, Alexander Dmitriev. "Prototype Development of EEG Acquisition System for Post-Stroke Rehabilitation Brain-Computer Interface: Preliminary Study", 2022 Ural-Siberian Conference on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT), 2022<br>Publication | <1% |
| 39 | Jean Li, Jeremiah D. Deng, Dirk De Ridder, Divya Adhia. "Gender Classification of EEG Signals using a Motif Attribute Classification Ensemble", 2020 International Joint Conference on Neural Networks (IJCNN), 2020<br>Publication | <1% |
| 40 | Marius Minea, Cătălin Marian Dumitrescu, Ilona Mădălina Costea. "Advanced e-Call | <1% |

Support Based on Non-Intrusive Driver Condition Monitoring for Connected and Autonomous Vehicles", Sensors, 2021
Publication

| | | |
|---|---|---|
| 41 | Md. Asif Ahamed, Md. Asraf-Ul Ahad, Md. Hanif Ali Sohag, Mohiuddin Ahmad. "Development of low cost wireless biosignal acquisition system for ECG EMG and EOG", 2015 2nd International Conference on Electrical Information and Communication Technologies (EICT), 2015<br>Publication | <1 % |
| 42 | ebin.pub<br>Internet Source | <1 % |
| 43 | mdpi-res.com<br>Internet Source | <1 % |
| 44 | "Digital Technologies and Applications", Springer Science and Business Media LLC, 2023<br>Publication | <1 % |
| 45 | "Intelligent Information and Database Systems", Springer Science and Business Media LLC, 2020<br>Publication | <1 % |

| | | | |
|---|---|---|---|
| Exclude quotes | On | Exclude matches | Off |

# CO-PO Mapping Justification Sheets

| PO | Levels 3/2/1 | Justification |
|---|---|---|
| **PO1** | 3 | Analog circuit design knowledge was used to design the circuit that could acquire the signal. Embedded C language was used to plot the signal on a serial monitor using Arduino UNO. |
| **PO2** | 2 | A common device that could acquire all three signals was not available. Hence, a circuit that could acquire all three signals was designed. |
| **PO3** | 2 | The device electrodes that are placed externally and does not cause harm to the subject and helps in safe acquisition of signals. |
| **PO4** | 3 | The research was conducted in designing a device to acquire signals. Efficient circuit was designed, and the output was plotted. |
| **PO5** | 2 | Simulation was performed using NI Multisim 14.2 and a dataset was provided for analysis using MATLAB. The acquired signal for the hardware was plotted on a serial plotter using Embedded C language. Arrhythmia and Seizure detection was performed using Machine learning. |
| **PO6** | 2 | An integrated system to record EEG, ECG, and EMG signals and hence work as a health monitoring device. |
| **PO7** | 3 | Different devices for different signal acquisition increases the usage of resources, hence developments have been made to reduce the resources. |
| **PO8** | 3 | In most cases, the software used was open-source, and credit has been given to the appropriate researchers. |
| **PO9** | 3 | Teamwork amplifies productivity through shared workloads, fuels innovation through collective ideas, and unlocks better ways to achieve goals through collaborative exploration. |
| **PO10** | 2 | Working in a team enhanced our communication skills, fostering effective collaboration with teammates, while also providing valuable opportunities to develop strong presentation skills for delivering impactful presentations to faculty, judges, and other stakeholders. |
| **PO11** | 3 | The project was efficiently executed, meeting all deadlines, and a well-prepared research report was submitted, with each team member assigned equal responsibilities. |
| **PO12** | 2 | Signal processing played a vital role in our analysis as it enabled us to effectively design and process biomedical signals. Additionally, we acquired expertise in utilizing machine learning and deep learning models for accurate disease detection. |
| **PSO1** | 3 | Hardware circuit that could acquire three biomedical signal ECG, EEG, EMG was designed and implemented |
| **PSO2** | 3 | Arduino was used to transmit analog signals to PC. Further, the signal was processed on MATLAB and used to detect Arrhythmia and Seizure using python. |

# Budget Estimation Sheets

| Sl. No. | Particulars | Estimated Cost in Rs. |
|---|---|---|
| 1 | Arduino Uno | 500 |
| 2 | TL074 Operational Amplifier | 12 |
| 3 | Resistors | 5 |
| 4 | Capacitors | 15 |
| 5 | Electrodes | 30 |
| 6 | Jumper wires and clips | 100 |
| 7 | Breadboard | 100 |
| 8 | PCB | 5200 |
| Total | | 5962 |